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A study on adaptive filtering for noise and echo cancellation.

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A Study on Adaptive Filtering for Noise and Echo Cancellation

by

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Abstract

The objective of this thesis is to investigate the adaptive filtering technique on the application of noise and echo cancellation. As a relatively new area in Digital Signal Processing (DSP), adaptive filters have gained a lot of popularity in the past several decades due to the advantages that they can deal with time-varying digital system and they do not require a priori knowledge of the statistics of the information to be processed. Adaptive filters have been successfully applied in a great many areas such as communications, speech processing, image processing, and noise/echo cancellation.

Since Bernard Widrow and his colleagues introduced adaptive filter in the 1960s, many researchers have been working on noise/echo cancellation by using adaptive filters with different algorithms. Among these algorithms, normalized least mean square (NLMS) provides an efficient and robust approach, in which the model parameters are obtained on the base of mean square error (MSE). The choice of a structure for the adaptive filters also plays an important role on the performance of the algorithm as a whole. For this purpose, two different filter structures: finite impulse response (FIR) filter and infinite impulse response (IIR) filter have been studied. The adaptive processes with two kinds of filter structures and the aforementioned algorithm have been implemented and simulated using Matlab.

Dedicated with love
to my parents,

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Contents

Abbreviations

DSP	Digital Signal Processing
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
LMS	Least Mean Square
NLMS	Normalized Least Mean Square
RLS	Recursive Least Square
FLMS	Fast Least Mean Square
DCT-LMS	Discrete Cosine Transform Least Mean Square
ANC	Adaptive Noise Canceller
MSE	Mean Square Error
SNR	Signal-to- Noise Ration
AEC	Adaptive Echo Canceller
ERLE	Echo Return Loss Enhancement

List of Figures

List of Tables

Chapter 1

Introduction

1-1 An Overview

Adaptive filtering, an advanced area in DSP, can be traced back to the late 1950s when a number of researchers were working on its theories and applications. It was the work of Dr. Bernard Widrow and his colleagues in this area that resulted in the famous Least Mean Square (LMS) algorithm in 1959 [1]. The field has been enjoying popularity since the mid-1970s primarily due to the advances in digital technology and the increase in research efforts, especially the developments in very large-scale integrated circuits (VLSI) and other digital hardware, which have made adaptive techniques feasible in real-time applications. Adaptive filtering has been successfully applied in a great many areas such as communications, speech processing, image processing and noise and echo cancellation, where a priori information about the statistics of the signal is not known completely.

1-2 Adaptive Filters and Adaptive Filtering Systems

1-2.1 Definitions of Adaptive Filters and Adaptive Filtering Systems

An adaptive filter is a time-variant filter whose coefficients are adjusted in a way to optimize a cost function or to satisfy some predetermined optimization criterion. An adaptive filtering system (usually contains adaptive filter) is a system whose structure is alterable or adjustable in such a way that its behavior or performance improves through contact with its environment.

1-2.2 Characteristics of Adaptive Filters [1]:

1. They can automatically adapt (self-optimize) in the face of changing (nonstationary) environments and changing system requirements.
2. They can be trained to perform specific filtering and decision-making tasks according to some updating equations (training rules).
3. They can usually be described as nonlinear systems with time-varying parameters.
4. Usually they are more complex and difficult to analyze than nonadaptive filters, but they offer the possibility to increase the system performance when input signal is unknown or time varying.

1-2.3 Block Diagram of an Adaptive Filter [3]

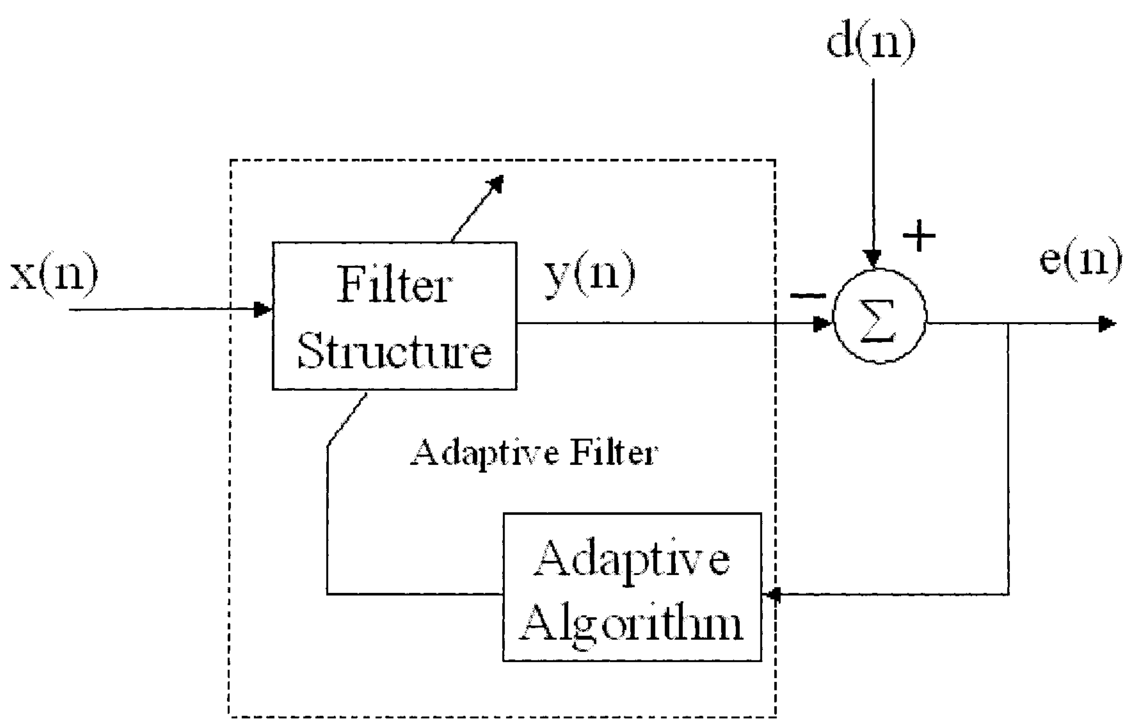

Figure 1.1 Block diagram of an adaptive filter

Figure 1.1 depicts the block diagram of an adaptive filter in the dashed line frame; it has six main components at time n:

(1) x(n): Input signal

(2) d(n): Desired signal

(3) y(n): Output signal

(4) e(n): Error signal

(5) Filter Structure: FIR or IIR or other various structures

(6) Adaptive Algorithm: determined by adaptive process criterion

At each iteration an input signal sample x(n) is processed by a time-varying filter to generate the output y(n). This signal is compared to the desired signal d(n) to generate an error signal e(n). This error signal e(n) which is the difference between the desired signal d(n) and the output signal y(n) is fed back to the adaptive algorithm to adjust the adaptive filter coefficients in order to minimize a given performance criterion or cost function. The minimization of the cost function implies that adaptive filter output signal is matching the desired signal in some sense according to different applications.

1-2.4 Filter Structure

Adaptive filters can be implemented in a number of different structures or realizations. The choice of the structure can influence the computational complexity of the process and also the necessary number of iterations to achieve a desired performance level.
Basically, there are two major classes of adaptive filter realizations, distinguished by the form of the impulse response, namely the finite-duration impulse response (FIR) filters and the infinite-duration impulse response (IIR) filters.

1-2.4.1 FIR Filter Structure

The most widely used adaptive FIR filter is the transversal filter, also called tapped delay line, depicted in Figure 1.2 [2]. There is an input signal vector with elements of N sequential samples from the same signal source **x**(n), a corresponding set of adjustable weights $w_0, w_1, \ldots, w_{N-1}$, N delay units and a single output signal, y(n). In this realization, the output signal y(n) is a linear combination of the filter coefficients, that yields a relatively straight forward construction of the filter. An N-Tap transversal was assumed as the basis for this adaptive filter. The value of N is determined by practical considerations. An FIR filter is chosen because of its unconditional stability and simplicity. Other alternative adaptive FIR realizations are also used in o rder to obtain improvements as compared to the transversal filter structure [4], [5].

In this thesis, transversal filter is used as the FIR filter structure.

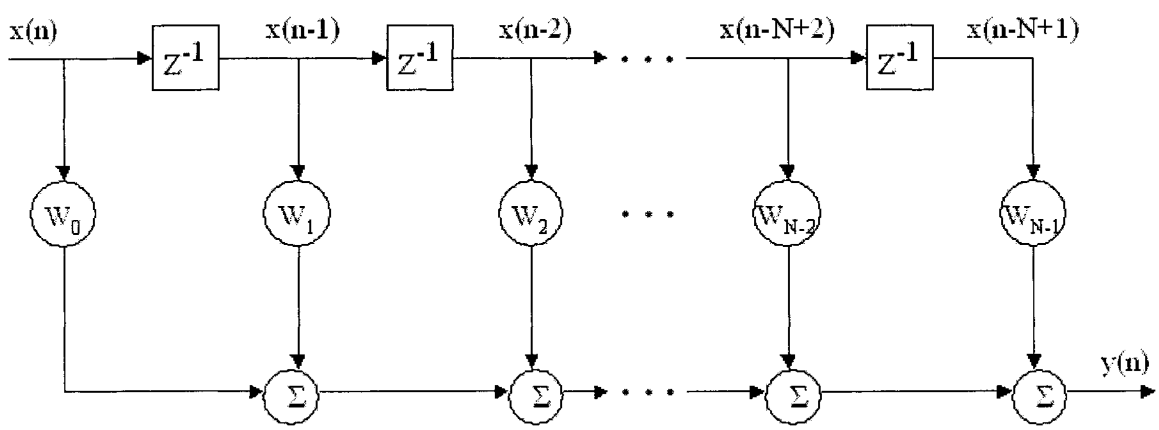

Figure 1.2 Transversal FIR filter structure

1-2.4.2 IIR Filter Structure

An IIR filter is chosen because its efficiency in modeling signals and smaller model order. The most widely used realization of adaptive IIR filter is the canonic direct-form realization, due to its simple implementation and analysis. Different realizations such as lattice [6], [7], cascade [8], and parallel [9] were also studied by researchers attempting to overcome the limitations of the direct-form structure.

In this thesis, direct-form IIR filter is used as IIR filter realization.

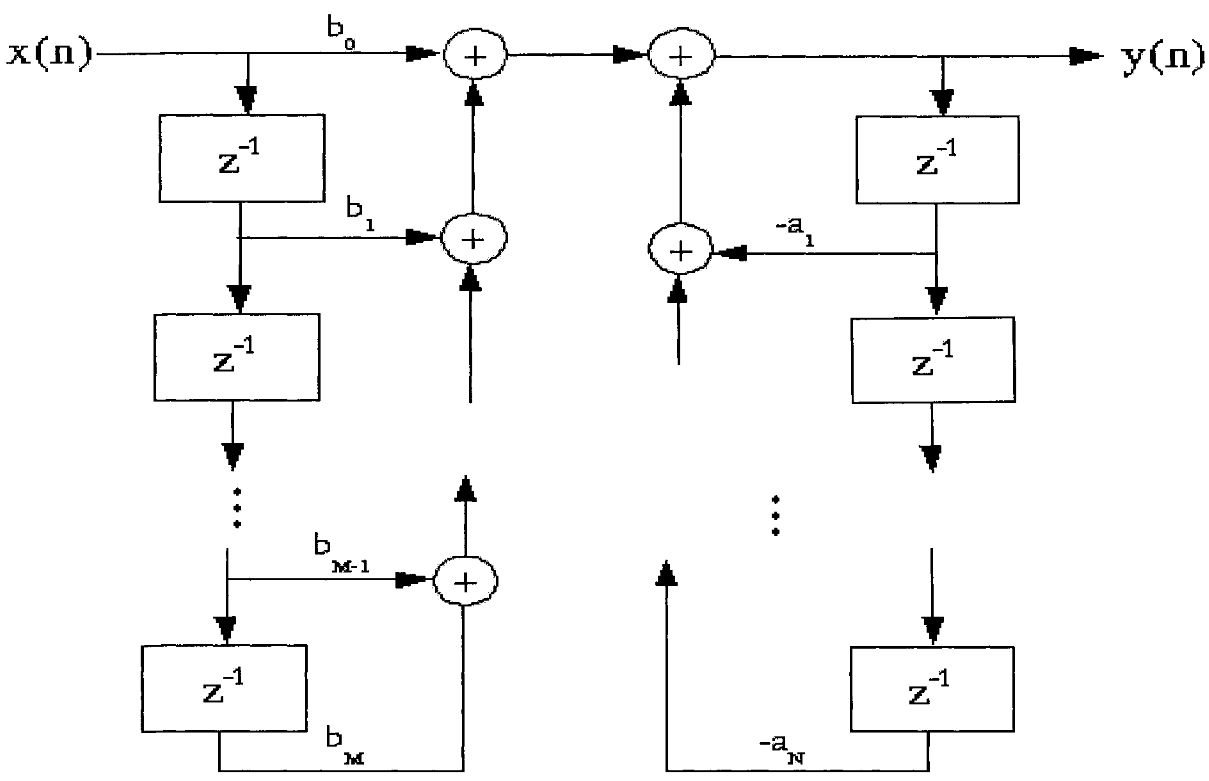

Figure 1.3 Direct-form IIR filter structure

1-2.5 Adaptive Algorithm

Adaptive algorithm is the procedure used to adjust the adaptive filter coefficients in order to minimize a prescribed criterion. The algorithm is determined by one or more of the following factors [2]:

- Rate of convergence. This is defined as the number of iterations required for the algorithm, in response to stationary inputs, to converge "close enough" to the optimum Wiener solution in the mean-square sense.

- Misadjustment. For an algorithm of interest, this parameter provides a quantitative measure of the amount by which the final value of the mean-squared error, averaged over an ensemble of adaptive filters, deviates from minimum mean squared error that is produced by the Wiener filter.

- Tracking. When an adaptive filtering algorithm operates in a nonstationary environment, the algorithm is required to track statistical variations in the environment.

- Robustness. For an adaptive filter to be robust, small disturbances can only result in small estimation errors.

- Computational requirements. This includes (a) the number of operations required to make one complete iteration of the algorithm, (b) the size of memory locations required to store the data and the program, and (c) the investment required to program the algorithm in a computer.

- Structure. This refers to the structure of information flow in the algorithm, determining the manner in which it is implemented in hardware form.

- Numerical properties. When an algorithm is implemented numerically, inaccuracies are produced due to quantization errors.

Various algorithms have developed in the past several decades since Widrow [1] and his co-workers in Stanford University originated Least Mean Square (LMS) algorithm. These algorithms fall into two categories: LMS algorithm family based on the Wiener filter theory and Recursive Least Squares (RLS) family based on the theory of Least Squares and Kalman filters. Among all these algorithms, the normalized LMS (NLMS) algorithm has gained wide popularity because of its simplicity and robustness.

In this thesis, NLMS is used as adaptive algorithm.

1-2.6 Adaptive Filtering Applications

The type of adaptive filtering application is defined by the choice of the signals acquired from the environment to be the input and desired-output signals. Applications of adaptive filtering cover a wide spectrum such as communication systems, control systems, seismology, biomedical electronics and various other systems in which statistical characteristics of the signals to be filtered are either unknown a priori or, in some cases, slowly time variant (nonstationary signals).

Basic classes of adaptive filtering applications include:

- System identification, in which an adaptive filter is used as a model to estimate the characteristics of an unknown system.

- Adaptive noise (interference) cancellation, in which an adaptive filter is used to estimate and eliminate a noise component in a desired signal.
- Echo cancellation, in which an adaptive filter is used to estimate the echo signal value and thus subtract it out.

1-3 Objectives of the Thesis

The work presented in this thesis bears two main objectives. One is to conduct a research study on the state of art adaptive noise/echo cancellation methods. Another one is to apply the normalized least mean square algorithm with two types of filter structure into the application of noise/echo cancellation.

1-4 Organization of the Thesis

This thesis is organized into six chapters. An overview of adaptive filtering on noise and echo cancellation is provided in Chapter 2. Various algorithms and methods from the early stage up to the recent work in this area will be discussed. The most popular NLMS algorithm is addressed.

In Chapter 3, Normalized Least Mean Square algorithm and its application to noise and acoustic echo cancellation are studied and evaluated.

In Chapter 4, the simulations and performance analysis of adaptive noise and echo cancellation by using FIR filter structure are presented.

In Chapter 5, the simulations and performance analysis of adaptive noise and echo cancellation by using IIR filter structure are given.

In Chapter 6, the performance comparison of adaptive FIR and IIR filter is discussed.

Finally, conclusions and future recommendations are made in chapter 7.

Chapter 2

Survey on Adaptive Noise and Echo Cancellation

2-1 Introduction

In this section, a comprehensive survey on the area of adaptive noise and echo cancellation is presented. It includes the approaches from the early stage up to the recent research work for using various adaptive algorithms and filter structures. We should emphasize that the list of methods included is not complete; rather the spectrum of possibilities in this area continually increases hand-in-hand with marketing strategies. Since echo cancellation can be treated as a special case of noise cancellation, we will focus on adaptive noise cancellation.

2-2 Brief History of Adaptive Noise Cancellation

The initial work started in 1965 when John Kelly and Ben Logan from Bell Telephone Laboratories proposed the use of an adaptive transversal filter for echo cancellation, with the speech signal itself utilized in performing the adaptation [2].

At the same time, an adaptive line enhancer was originated by Bernard Widrow and his co-workers at Stanford University [30]. The first version of this device was built to cancel 60 Hz interference at the output of an electrocardiographic amplifier and recorder. These two major works, although intended for different applications, were viewed as the

Adaptive Noise Canceller scheme discussed by Widrow et al [30] in 1975. The scheme refers to situations where it is required to cancel an interfering signal or noise from a given signal, which is a mixture of the desired signal and interfering signal.

2-3 Adaptive Noise Cancellation

2-3.1 Description of Adaptive Noise Canceller

Adaptive noise cancellation is the process of removing noise or distortion from a received signal in an adaptive manner for the purpose of improved signal-to-noise ratio. The block diagram of an adaptive noise canceller (ANC) is depicted in Figure 2.1.

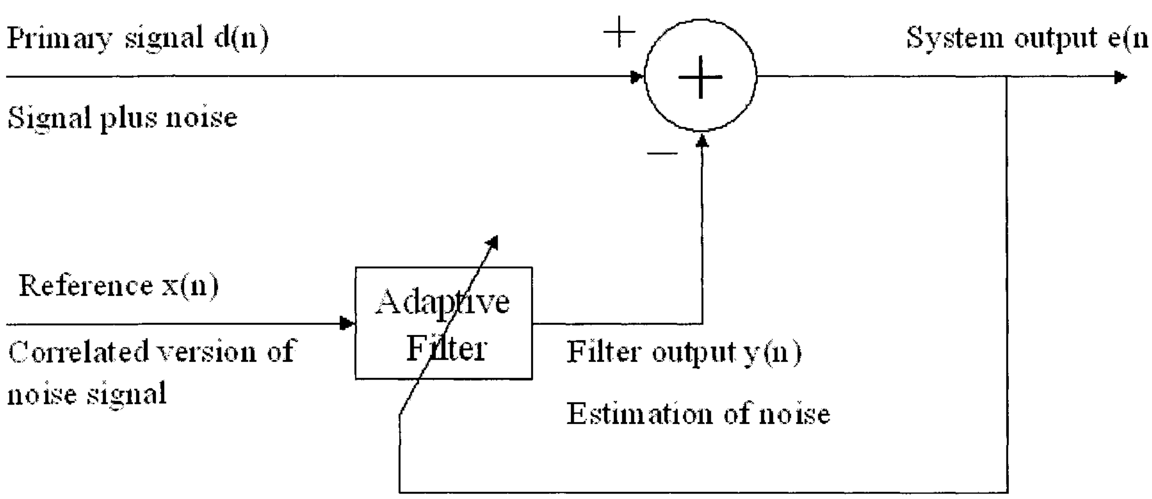

Figure 2.1 Block diagram of adaptive noise canceller

Basically an adaptive noise canceller has two inputs [2]:

1. The main (primary or desired) input containing the information-bearing signal $s(n)$ which is corrupted by background noise $x'(n)$, can be expressed as

$$d(n) = s(n) + x'(n) \tag{1}$$

The signal $s(n)$ and the noise $x'(n)$ are uncorrelated with each other; that is

$$E[s(n)x'(n - k)] = 0 \quad \textit{for all } k \tag{2}$$

where k is 0, 1, …, N-1.

2. The other input (noise reference input) contains noise $x(n)$ correlated with the background noise $x'(n)$ in some way, but uncorrelated with the signal $s(n)$; that is,

$$E[s(n)x(n - k)] = 0 \qquad \textit{for all } k \tag{3}$$

and

$$E[x'(n)x(n - k)] = p(k) \tag{4}$$

where $p(k)$ is an unknown cross-correlation for lag k.

The reference input $x(n)$ is processed by an adaptive filter to produce the output signal:

$$y(n) = \sum_{k=0}^{N-1} w_k(n)x(n-k) \tag{5}$$

where $w_k(n)$ are the adjustable tap weights of the adaptive filter.

The filter output $y(n)$ is subtracted from the main input signal $d(n)$. The error signal is defined by

$$e(n) = d(n) - y(n) \tag{6}$$

Substituting Eq. (1) into (6), we get

$$e(n) = s(n) + x'(n) - x(n) \tag{7}$$

2-3.2 Surveys of Adaptive Algorithms for FIR filtering

As shown in Figure 2.1, the adaptive filter is the main component in ANC system. From Chapter 1, we know that an adaptive filter is composed of a filter structure and an algorithm. The performance of an adaptive filter is critically depending not only on its internal structure, but also on the algorithm [1, 2] used to recursively update the filter coefficients that define the filter structure. In this section we focus on adaptive filter with FIR structure. The coefficients update can be described in words generally as follows:

new coefficients = old coefficients + (learning rate) (input) (error signal)

Many new algorithms have developed since the least mean square (LMS) was proposed by Widrow [1] for different purposes. These algorithms can be categorized roughly into two families: LMS based algorithm and recursive least mean square (RLS) based algorithm.

In LMS family, first a modified LMS called normalized LMS (NLMS) algorithm is developed [52, 53]. The NLMS algorithm modifies the coefficient update process such that it is normalized with respected to the input signal's power [2, 31]. The NLMS is more robust than its unnormalized counterpart and shows an improved convergence behavior [32]. The convergence rate of all the LMS family is heavily dependent on the eigenvalue distribution of the autocorrelation matrix of the input signal. To accelerate the convergence speed of this kind algorithm and at the same time keep the computational complexity at a low level, several methods have been proposed by preconditioning, e.g., pre-whitening or decorrelating input data [1,33]. The basic version of this approach is that one filter is used for the NLMS adaptation process and other one performs the actual noise/echo cancellation. The demerits of this approach are the requirement of highly precise computation and its complexity. Many algorithms are proposed to improve the convergence speed by controlling the step size. An algorithm whose step size is controlled by using the square of the output error is presented by Casco et al in [60]. Kim and Poularikas [61] proposed an adjusted step size LMS algorithm. This algorithm updates a coefficient by a different step size which is controlled by signal to noise ratio to improve the performance of adaptive FIR filters in nonstationary environments.

All of the above approaches to improve the behavior of the LMS algorithm are operating in the time domain. However transform domain LMS (TDLMS) is to use the frequency domain to decorrelate the input signal of LMS algorithm [34, 35]. That the Fourier analysis is approximated by the Discrete Fourier Transform (DFT) is also can be used to decorrelate the input signal [36]. Wavelet transform domain adaptive algorithms are presented in [37]. Other LMS based algorithms are described by Glentis in [54].

After these researches, other algorithms that are not based on the LMS algorithm are presented. One of them is the well known recursive least square (RLS) algorithm [2], as opposed to the LMS algorithm, the expected value of squared error is not approximated by the instantaneous value of squared error but computed by averaging several samples of squared error. It has been shown that the RLS algorithm is superior to the NLMS algorithm in terms of convergence speed and also tracking speed if the eigenvalue spread of the input correlation matrix is large [32]. For these merits, extensive research has been going on to compute the RLS problem by fast algorithm like fast transversal filters (FTFs) [38]. However RLS and FTFs have the disadvantages of requiring high numerical precision and numerical instabilities so that the filters have to be reinitialized [39]. To compensate the demerits of RLS and FTFs, fast Newton filters [40, 41] and affine projection algorithm (APA) [42] are presented. Other, low complexity, quasi-Newton adaptive algorithms have been developed by proper choice of the weight matrix [43]. A fast RLS algorithm is shown in [44].

Since speech is a wideband signal with continuously changing spectral contents and the full-band filtering has several problems such as insufficient convergence speed, high numerical precision, instability of RLS and requirement of expensive computation processor, the sub-band filtering method is introduced [45, 46]. This method puts the signals into several frequency bands and employs independently operating adaptive filters within each sub-band. This method improves convergence speed and reduces the sampling rate within the sub-bands to save computational effort and to reduce the filter length of the sub-band adaptive filters.

A large number of block-adaptive-filtering algorithms have also been developed in the past two decades [47, 48, 49]. The block-adaptive techniques can be classified as frequency (or transform) domain and time domain. The transform domain techniques have been summarized in a paper by Shynk [50] in 1992. The distinctive trait of the block-exact adaptive techniques [51] is that the same estimates are obtained at a substantially reduced complexity compare with their counterparts.

The performance of some algorithms is given in Table 2-1.

Table 2-1 Performance comparison of adaptive algorithms

Algorithm	LMS	NLMS	RLS
Convergence time	Very slow	Slow	Fast
Stability	Very stable	Stable	Very unstable
Complexity	Very simple	Simple	High
Implementation	Very simple	Simple	Difficult

2-3.3 Adaptive algorithms for IIR Filtering

Though the design theory of FIR filtering is well mastered and applied in many areas, practical experience with adaptive FIR filtering has also revealed performance limitations that might be overcome with IIR filtering [12, 15, 27]. These limitations have become particularly apparent upon modeling acoustic impulse responses that arise in echo cancellers, or physical and industrial processes that are the domain of control engineers. IIR adaptive filters adjust rational transfer functions; in contrast to their FIR counterparts which adjust polynomial transfer functions. The fact that rational functions are more versatile and powerful in modeling than polynomial functions has made many researchers aim to show performance improvements obtained from adaptive IIR filters, compared to adaptive FIR filters. However, such performance improvements have not been demonstrated satisfactorily [12, 15, 27].

Some valuable general papers on the topic of adaptive IIR filtering are presented by Johnson [12], Shynk [13], and Netto [14]. Johnson's paper focused on the common theoretical basis between adaptive IIR filtering and system identification. Shynk's paper dealt with various algorithms of adaptive IIR filtering for their error formula and realization. Netto's paper presented the characteristics of the most commonly used algorithms for adaptive IIR filtering in a simple and unified framework. And Regalia published a full book on IIR filters [15]. Literature about adaptive IIR filtering can be classified into three categories: adaptive IIR filter structures, adaptive algorithms, and applications.

Adaptive IIR filter structure. The choice of the adaptive filter structures affects the computational complexity and the convergence speed. White [18] first presented an implementation of an adaptive IIR filter structure. Later, many articles were published in this area. Canonic direct form is the most used realization in adaptive IIR filter for its simple implementation and easy analysis. However, some disadvantages of the direct form such as finite-precision effects, slow convergence and the complexity of stability monitoring have led to the alternative structures [55]. Commonly used structures are cascade [19], lattice [17], and parallel [9] structures.

- **Algorithms.** The algorithm determines several important features of the whole adaptive procedure, such as computational complexity, convergence speed, objective cost function and error signal. The most commonly known approaches to adaptive IIR filtering that correspond to different formulations are equation error method [56], output error method [2, 57], and composite method [20].

— In the equation error formulation, the feedback coefficients of an IIR filter are updated in an all-zero, nonrecursive form which is then copied to a second filter implemented in an all-pole form. This formulation is essentially a type of adaptive FIR filtering, and the corresponding algorithms have properties that are well understood and predictable. The main characteristics of the equation error method are unimodality of the Mean-Square-Error (MSE) performance surface, good convergence, and guaranteed stability. Unfortunately, the equation error approach can lead to biased estimates of the coefficients.

— The output error formulation updates the feedback coefficients directly in a pole-zero, recursive form and it does not generate biased estimates. The main characteristics of the output-error method are the possible existence of the multiple local minima, which affect the convergence speed and the requirement of stability checking during the adaptive processing.

— The composite error algorithm attempts to combine the good individual characteristics of both output error algorithm and equation error algorithm [21].

- **Application.** Adaptive IIR filtering has been successful in many applications, such as echo cancellation, noise cancellation, system identification, and control.

In this thesis we use the output error method based on NLMS algorithm and the direct form realization of IIR filter for noise and echo cancellation.

2-4 NLMS algorithm for noise and echo cancellation

From Table 2-1 we can see that NLMS algorithm is characterized by its simplicity and robustness, which has made NLMS the standard against other adaptive algorithms compared [2]. Nagumo and Noda were the first to introduce the normalized LMS algorithm for learning identification under non-stationary random inputs [52], and independently by Albert and Gardner in 1967 [53], but they did not use the name of "NLMS". It appears that Bitmead and Anderson (1980) coined the name "normalized LMS algorithm" [2]. After this many modified NLMS algorithms have been proposed for different applications and purposes. An adjusted step size NLMS algorithm based on ratio of the average power of the original signal to the average power of the noise signal was proposed in [58]. A NLMS-neural network method was discussed in [59] to improve the Echo Return Loss Enhancement performance.

In this thesis, we use NLMS algorithm both in adaptive FIR filter and IIR filter. In Chapter 3 we will study NLMS algorithm in detail.

Chapter 3

The Normalized Least Mean Square (NLMS) Algorithm

3-1 Introduction

Normalized Least-Mean-Square (NLMS) algorithm can be viewed as a special implementation of the Least Mean Square algorithm which takes into account the variation in the signal level at the filter input and selects a normalized step-size parameter which results in a stable as well as fast converging adaptive algorithm [11]. Before we discuss NLMS algorithm, we have to give the derivation of the LMS algorithm.

3-2 Least-Mean-Square (LMS) Algorithm

3-2.1 Background

The LMS algorithm was devised by Widrow and Hoff in 1959 in their study of a pattern-recognition machine known as the adaptive linear element, commonly referred to as Adaline. It is one of the most popular adaptive algorithms for noise and echo cancellation due to its computational simplicity (Widrow, 1985), proof of convergence, unbiased convergence in the mean and robust to hardware arithmetic computation (e.g. fixed-point arithmetic and word length effect).

The LMS algorithm is an iterative solution based on the steepest descent approach in that it uses a special estimate of the gradient to replace the gradient vector that characterizes the method of steepest descent. Then the tap weights are adapted (approaches the Wiener solution as the number of iterations increases to infinity) according to the steepest descent type of adaptive algorithm and the expected value of squared error is minimized. As the tap weights are adjusted, the filter learns the characteristics of the signal. The basic components of the process are illustrated in Figure 3.1.

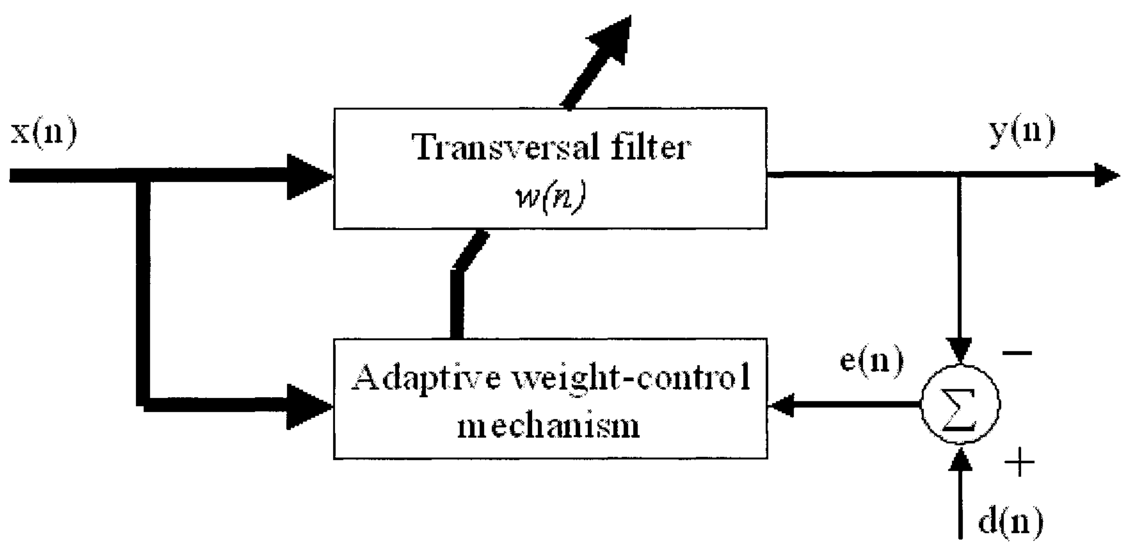

Figure 3.1 Block diagram of adaptive transversal filter

3-2.2 Description

From Figure 3.1, it is be observed that the LMS algorithm consists of two basic processes [2]:

1. A *filtering process*, which involves (a) computing the output of the transversal filter in response to an input signal and (b) generation an estimation error by comparing this output with a desired response.

2. An *adaptive process*, which involves the automatic adjustment of the filter in accordance with the estimation error.

In Figure 3.1, four signals are defined:

(1) $\mathbf{x}(n)$: the vector of tap inputs

$$\mathbf{x}(n) = [\,x(n)\;\; x(n\text{-}1)\;\; x(n\text{-}2)\;\; \ldots\;\; x(n\text{-}N\text{+}1)]^T \qquad (3.1)$$

where the superscript T denotes transpose, $\mathbf{x}(n)$ is a N-by-1 vector and N is the tap number.

(2) $d(n)$: desired response at time n

(3) $y(n)$: output of the filter at time n (the estimate of the desired response in some applications)

$$y(n) = \mathbf{w}^H(n)\,\mathbf{x}(n) \qquad (3.2)$$

where $\mathbf{w}(n)$ is the N-by-1 weight vector at time n in Figure 3.1.

$$\mathbf{w}(n) = [w_0(n)\;\; w_1(n)\;\; w_2(n)\;\; \ldots\;\; w_{N-1}(n)]^T \qquad (3.3)$$

where the superscript H denotes the *Hermitian Transposition* which consists of the operation of transposition combined with complex conjugation.

(4) $e(n)$: estimation error at time n

$$e(n) = d(n) - y(n) \qquad (3.4)$$

substituting (3.2) into (3.4), we get

$$e(n) = d(n) - \mathbf{w}^H(n)\mathbf{x}(n) \tag{3.5}$$

As mentioned earlier on, the LMS algorithm is based on steepest descent approach (for simplicity assume the tap input vector **x**(n) and the desired response d(n) are jointly stationary) to minimize expected value of squared error. Thus the cost function, mean squared error is,

$$J(n) = \mathbf{E}[\, e(n)e^*(n)] = \mathbf{E}[|e(n)|^2] \tag{3.6}$$

where **E** [] is the expected value, the superscript * denotes the complex conjugate. By using steepest descent method, the tap weights are computed in a direction opposite to that of the gradient vector (the derivative of the mean squared error J(n) evaluated with respect to the tap-weight vector **w**(n)) and will eventually converge to the optimum Wiener solution.

According to the method of steepest descent, at time n+1, the tap weights are updated in a simple recursive way [2]:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu[-\nabla J(n)] \tag{3.7}$$

where μ is a positive constant which is called step size and $\nabla J(n)$ is the gradient at time n. The gradient vector $\nabla \mathbf{J}(n)$ is defined as [2]:

$$\nabla \mathbf{J}(n) = -2\boldsymbol{P} - 2\boldsymbol{R}(n)\,\mathbf{w}\,(n) \tag{3.8}$$

where $\boldsymbol{P}$ is the cross-correlation vector between the tap inputs $\mathbf{x}(n)$ and the desired response $d(n)$ and $\boldsymbol{R}$ is the correlation matrix of the input vector $\mathbf{x}(n)$. For simplicity, $\boldsymbol{P}$ and $\boldsymbol{R}$ are estimated by using instantaneous estimates defined respectively as

$$\hat{P} = \mathbf{x}(n)d^*(n) \tag{3.9}$$

$$\hat{R} = \mathbf{x}(n)\mathbf{x}^{H}(n) \tag{3.10}$$

Substituting equations (3.8), (3.9) and (3.10) into equation (3.7) yields the LMS adaptation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\,\mu\mathbf{x}(n)[d^{*}(n) - \mathbf{x}^{H}(n)\,\mathbf{w}(n)]. \tag{3.11}$$

Uniting equation (3.5) and (3.11), we get the LMS algorithm

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e^{*}(n)\mathbf{x}(n) \tag{3.12}$$

Equation (3.12) illustrates the simplicity of the LMS algorithm, For each iteration the LMS algorithm requires 2N additions and 2N+1 multiplications (N for calculating the output, $y(n)$, one for $\mu e(n)$ and an additional N for the scalar by vector multiplication) [11], so the computational complexity of the LMS algorithm is O(N), where N is the number of tap weights used in adaptive transversal filter.

Figure 3.2 presents a flowchart of the LMS algorithm.

3-2.3 Stability of the LMS Algorithm

Since the LMS algorithm has the existence of feedback, it may cause the algorithm to be unstable. In order to make the algorithm converge to the optimum Wiener solution, the step-size parameter μ should satisfy the following condition [2]:

$$0 < \mu < \frac{2}{\lambda_{\max}} \tag{3.13}$$

where λ_{max} is the largest eigenvalue of the correlation matrix $\boldsymbol{R}$ as defined earlier. Since the eigenvalues are not easily available, a practical definition for λ_{max} is:

$$\lambda_{max} < tr[\boldsymbol{R}] \tag{3.14}$$

Therefore, the alternative of $\frac{1}{tr[R]}$ is a sufficient condition to ensure stability. The maximum eigenvalues determine the upper bound operation condition, while the smallest eigenvalues in $\boldsymbol{R}$ are responsible for the slowest convergence. The mean convergence of the LMS and upper bound step size have shown that the convergence characteristics are sensitive to the condition of the correlation matrix **R** or the second order statistics of the input signal.

3-2.4 Learning Curve of the LMS Algorithm

One of the performance measures of the LMS algorithm is the learning curve (also called output estimation error) that defined as

$$\text{Output Estimation Error} = 20\log_{10}(|e(n)|) \tag{3.15}$$

3-2.5 Disadvantages of the LMS Algorithm

Two major drawbacks of the LMS Algorithm are [2]:

- slow rate of convergence, the convergence rate is highly dependent on the step size parameter μ.
- sensitivity to the eigenvalue spread (which is the ratio of the largest eigenvalue to the smallest eigenvalue) of the correlation matrix $\boldsymbol{R}$.

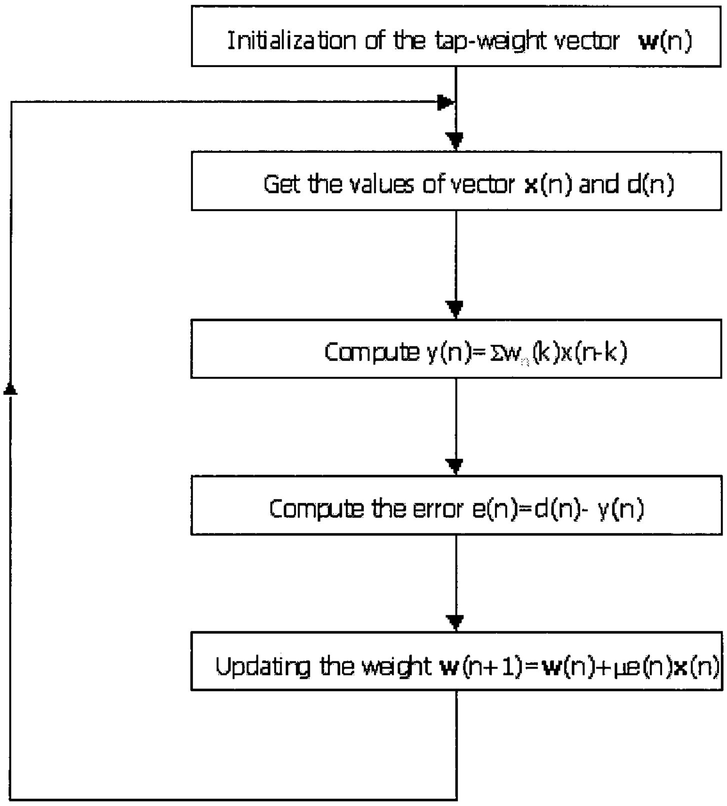

Figure 3.2 Flowchart of the LMS algorithm

3-3 Normalized LMS Algorithm (NLMS)

3-3.1 Derivation of Normalized LMS Algorithm [2]

In the LMS algorithm studied earlier, the adjustment applied to the tap-weight vector at iteration n+1 consists of the product of three terms: the step-size parameter μ, the input vector $\mathbf{x}(n)$ and the estimation error $e(n)$. The adjustment is directly proportional to the input vector $\mathbf{x}(n)$. Therefore, when $\mathbf{x}(n)$ is large, the LMS algorithm suffers from a gradient estimation error. To overcome this difficulty, we can use the normalized LMS algorithm. In particular, the adjustment applied to the tap-weight vector at iteration n+1 is "normalized" with respect to the squared Euclidean norm of the input vector **x**(n) at iteration n—hence the term "normalized."

The μ in equation (3.12) is replaced by a normalized value of μ as

$$\mu(\mathrm{n}) = \frac{\mu}{\alpha + \|x(n)\|^2} \tag{3.16}$$

where α is a small value number used to overcome the numerical difficulties when input **x**(n) is small and $||\mathbf{x}(n)||^2$ is the Euclidean norm of the input vector **x**(n)

This modified version of LMS algorithm is called the Normalized LMS (NLMS) algorithm.

3-3.2 Summary of the NLMS Algorithm

As the NLMS algorithm is a modified version of LMS algorithm, the flowchart of NLMS is very similar to that of the LMS algorithm. Figure 3.3 depicts the flowchart of NLMS.

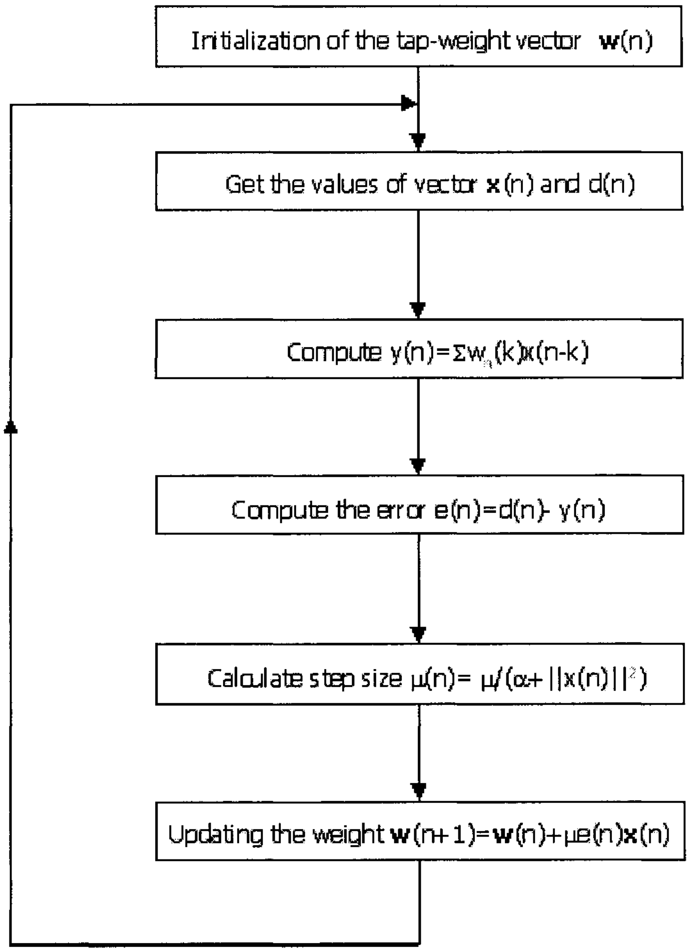

Figure 3.3 Flowchart of the NLMS algorithm

Chapter 4

FIR Adaptive Noise and Echo Cancellation

4-1 Introduction

Noise and echo cancellation are basic problems in many engineering, important applications in digital voice communication system are to extract the desired speech signal from the noisy one and remove the noise or echo. Adaptive FIR filter is widely used in these areas due to its unconditional stability and simple implementation. The NLMS algorithm is popular for its simplicity and numerical stability. We described the basic concepts of adaptive filtering and adaptation algorithm in the first two chapters, this chapter we will use adaptive FIR filter structure and NLMS algorithm to reduce the noise and remove echo in speech signal.

4-2 FIR Adaptive Noise Cancellation

4-2.1 Introduction

Extracting a desired speech signal from noisy speech corrupted by additive noise is an important problem in digital voice communication systems. The background noise is encountered in such environments as airplane, automobiles and helicopters. Adaptive noise canceller (ANC) is a powerful approach to reduce noise. In ANC, there are two microphones: the primary microphone is used to obtain the noise-corrupt speech and the reference microphone is used to obtain only a correlated component of the noise in the primary microphone. The noise in the reference microphone is processed by the adaptive filter to generate a replica of the noise component in the primary input. Figure 4.1 constructs the FIR adaptive noise canceller using NLMS algorithm.

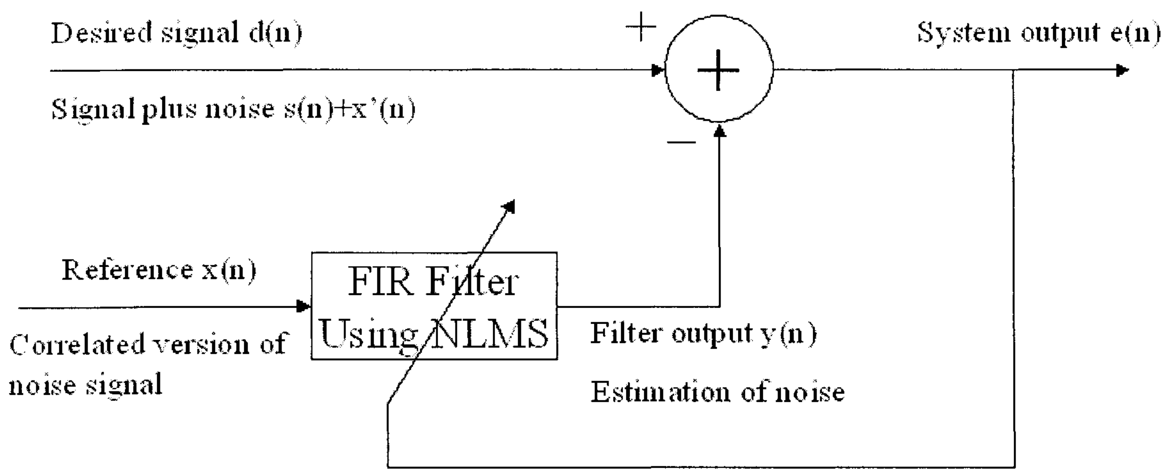

Figure 4.1 Adaptive FIR noise cancellation using NLMS

4-2.2 Derivation of Adaptive FIR Algorithm

For the NLMS algorithm, the filter structure in Figure 4.1 is a time-varying FIR filter. The input-output relationship is described by

$$y(n) = \sum_{i=0}^{N-1} W_i(n) X(n-i) \tag{4.1}$$

where the time-varying character of the filter coefficients is signified by the $W_i(n)$ notation.

The goal of the adaptive process is to adjust the filter coefficients in such a way that the error

$$e(n) = d(n) - y(n) \tag{4.2}$$

is minimized in some sense. Where $e(n)$, $d(n)$ and $y(n)$ are as defined in Fig.4.1.

As we discussed in Chapter 3, the LMS algorithm is based on steepest descent to update filter coefficients. It simply replaces the cost function $\xi=E[e^2(n)]$ by its instantaneous coarse estimate $\hat{\xi} = e^2(n)$. The update of the filter coefficient can be described in vector form as follows:

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu\nabla e^2(n) \tag{4.3}$$

where

Coefficient vectoris $\mathbf{w}(n) = [w_0(n) \;\; w_1(n) \;\; w_2(n) \;\; \ldots \;\; w_{N-1}(n)]^T$,

$$\text{Gradient vector is } \nabla = [\frac{\partial}{\partial w_0} \;\; \frac{\partial}{\partial w_1} \;\; \cdots \;\; \frac{\partial}{\partial w_{N-1}}]^T, \tag{4.4}$$

and μ is the the algorithm convergence parameter.

We note that the ith element of the gradient vector $\nabla e^2(n)$ is

$$\begin{aligned} \frac{\partial e^2(n)}{\partial w_i} &= 2e(n)\frac{\partial e(n)}{\partial w_i} \\ &= 2e(n)\frac{\partial(d(n)-y(n))}{\partial w_i}. \end{aligned} \tag{4.5}$$

Since $d(n)$ is independent of w_i, we obtain

$$\frac{\partial e^2(n)}{\partial w_i} = -2e(n)\frac{\partial y(n)}{\partial w_i} \tag{4.6}$$

Substituting for $y(n)$ from (4.1) we get

$$\frac{\partial e^2(n)}{\partial w_i} = -2e(n)x(n-i) \tag{4.7}$$

combining (4.4) and (4.7) we obtain

$$\nabla e^2(n) = -2e(n)\mathrm{x}(n) \tag{4.8}$$

substituting this result in (4.3), we get the LMS algorithm as follows:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu e(n)\mathbf{x}(n) \tag{4.9}$$

where $x(n)$ is a vector of input signal values,

$$\mathbf{x}(n) = [\,x\,(n)\;\; x\,(n-1)\;\; x\,(n-2)\;\; \ldots\;\; x\,(n-N+1)]^T$$

From (4.9) we see that given an input signal $\mathbf{x}(n)$ and a primary signal $d(n)$, the implementation of the LMS adaptive algorithm requires only the selection of the convergence parameter μ . This convergence parameter plays an important role in determining the performance of an adaptive system [1]. It has been shown that the stable range of μ varies according to the input signal power [1]. In place of μ in (4.9), we use the normalized value

$$\mu \leftarrow \frac{\mu}{(L+1)\sigma^2} \tag{4.10}$$

where L+1 is the number of filter coefficients and σ^2 is the input signal power. We can show that the stable range of μ is always $0< \mu <1$[66].

In some applications, the input signal power is either unknown or is changing with time in a nonstationary environment. In such cases, the σ^2 in (4.10) can be replaced by a time-varying estimate

$$\sigma^2(n) = \alpha x^2(n) + (1-\alpha)\sigma^2(n-1) \tag{4.11}$$

where $x(n)$ is the current input sample and α is a forgetting factor in the range $0< \alpha << 1$[66].

In this thesis, the NLMS algorithm is utilized in the following form

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{2\mu e(n)}{(L+1)\sigma^2(n)}\mathbf{x}(n) \qquad 0< \mu <1 \tag{4.12}$$

$$\sigma^2(n) = \alpha x^2(n) + (1-\alpha)\sigma^2(n-1) \qquad 0< \alpha << 1 \tag{4.13}$$

4-2.3 Performance Measures

Some of the useful tools to express the effect of noise cancellation are defined in this section.

4-2.3.1 MSE (Mean-Square Error)

The mean-square error (MSE), is also called learning curve, is the squared value of the difference between the primary signal d(n) and the estimated filter output y(n), defined as

$$\begin{aligned} \text{MSE} &= E\,[e(n)e^*(n)] \\ &= E\,[|e(n)|^2] \\ &= E\,[|d(n)-y(n)|^2] \end{aligned} \tag{4.14}$$

where E denotes the statistical expectation operator, in this thesis we use the norm function in Matlab to calculate the MSE.

4-2.3.2 SNR (Signal- to- Noise Ratio)

Signal- to-noise ration (SNR) is a measurement of the level of noise between the signal and noise in decibel (dB), defined as

$$SNR = 10\log_{10}(P_S/P_N) \text{ (dB)} \tag{4.15}$$

where P_S and P_N are the powers of the signal and noise respectively, they are defined as

$$P_S = \sum_{n=1}^{N} s^2(n) \tag{4.16}$$

$$P_N = \sum_{n=1}^{N} x^2(n) \tag{4.17}$$

Where *s(n)* is the noise-free signal, *x(n)* is the reference noise signal as shown in Figure 4.1. N is the total number of samples in *s(n)* and *x(n)* within the given measurement period.

4-2.4 Signals

The signals that are used in this thesis are defined in this section. These signals include three noise-free speech signals and three types of noise signal: sinusoidal signal, white noise signal and colored noise signal.

4-2.4.1 Speech Signals

The speech signals, i.e. the digitized loaded wave files, are used as noise-free signals. The description of the speech signals used in this thesis is illustrated in Table 4-1.

Table 4-1: Descriptions of Speech signals

Name	Sex	Sentence	Sampling Frequency	Length
S1.wave	Male	What is this	11 kHz	10385
S2.wave	Male	The discrete for a transformed real value signal was contradict symmetric	22 kHz	110033
S3.wave	Female	Think of a bottle of water, think of a white sky, think of a boat, think of a balloon blowing by	8 kHz	52560

Different speech signals are chosen from different speakers to evaluate and compare the performance of noise/echo cancellation. The three speech signals are plotted in Figures 4.2 to 4.4. These three speech signals are used as noise-free signal in this thesis.

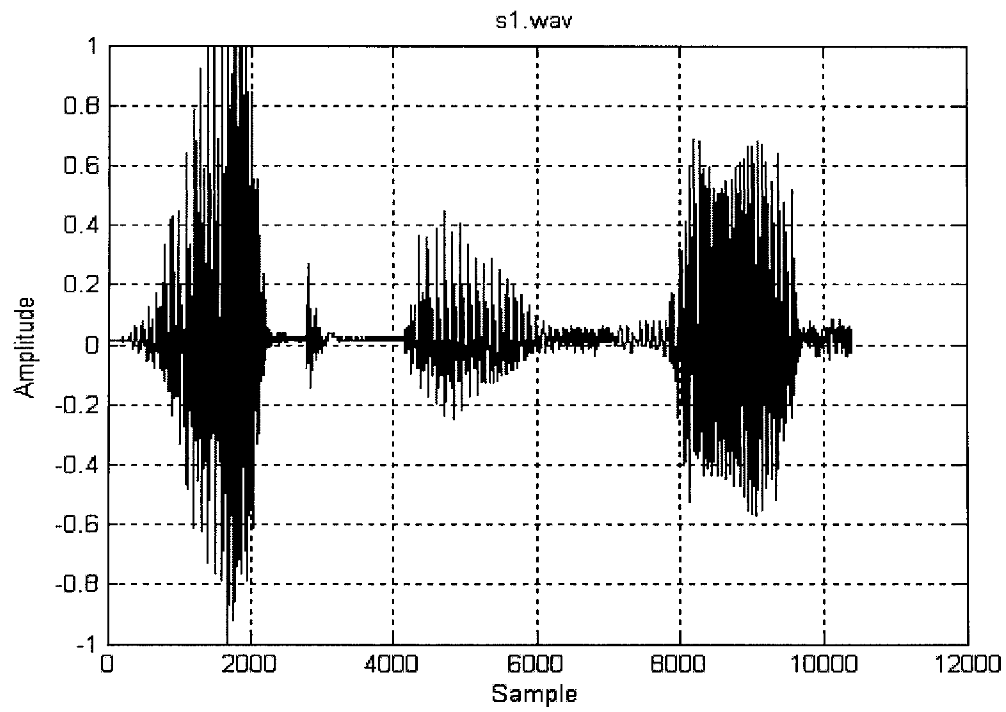

Figure 4.2 S1.wave speech signal

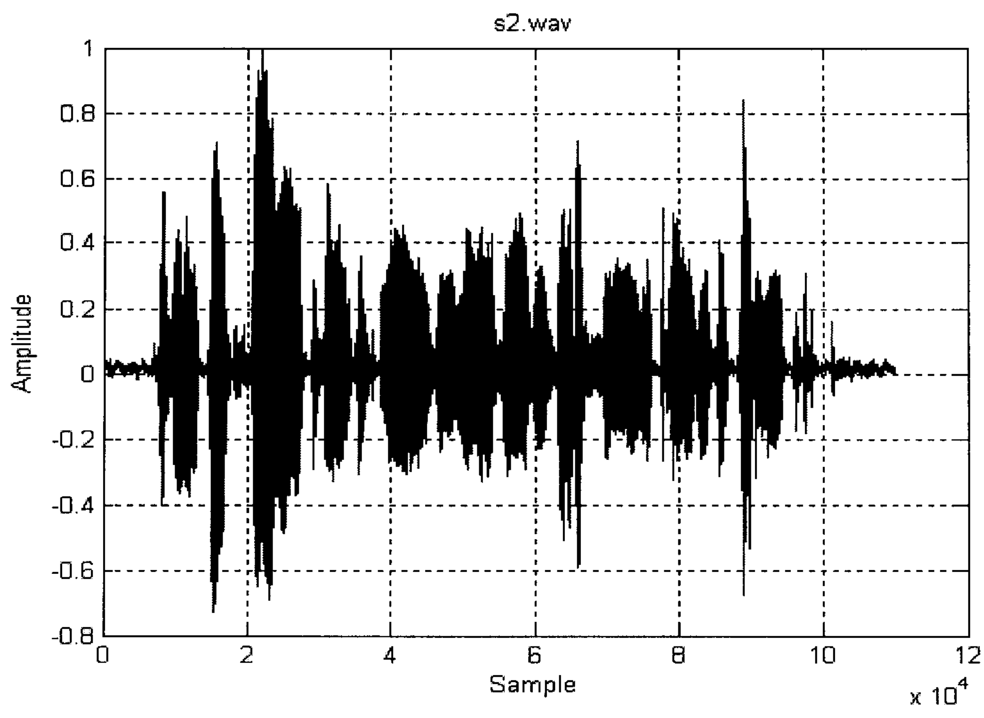

Figure 4.3 S2.wave speech signal

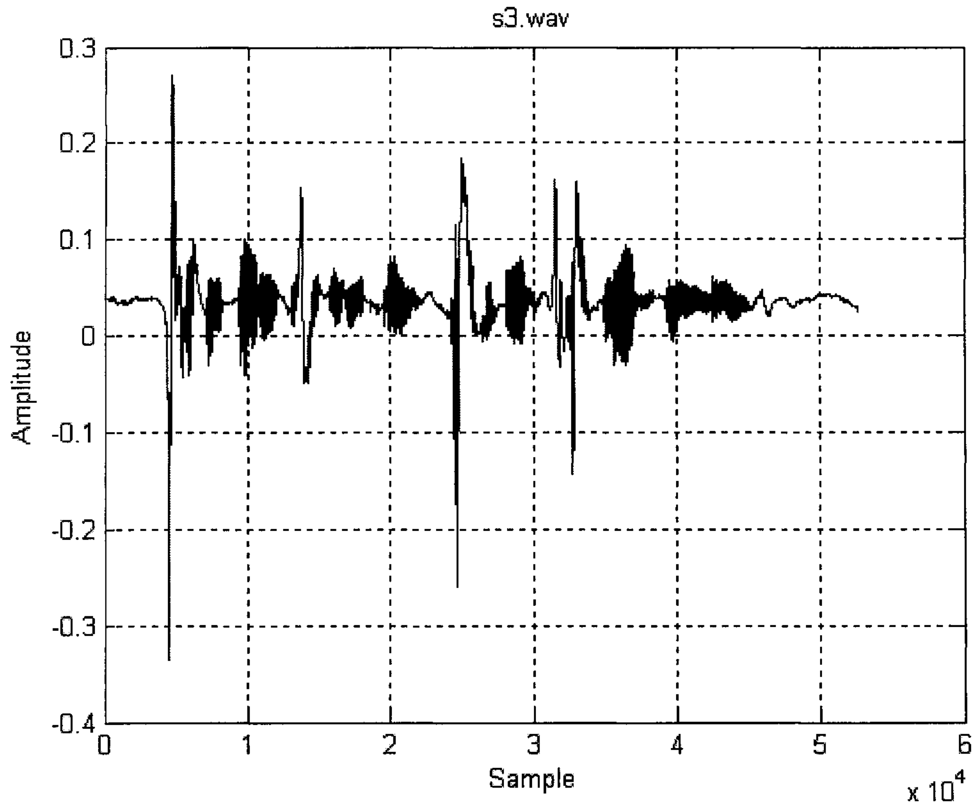

Figure 4.4 S3.wave speech signal

4-2.4.2 Sinusoidal Noise Signal

The single frequency sinusoidal signal with frequency f=600 Hz is used as a noise signal in this thesis, it is defined as

$$x(n)=\mathrm{A}\sin\left(2\pi\frac{f}{f_s}n\right) \tag{4.18}$$

where f_s is the sampling frequency, and A is the amplitude of the signal. Figure 4.5 plotted the frequency response of the single frequency sine signal under different sampling frequencies when applied with different speech signals.

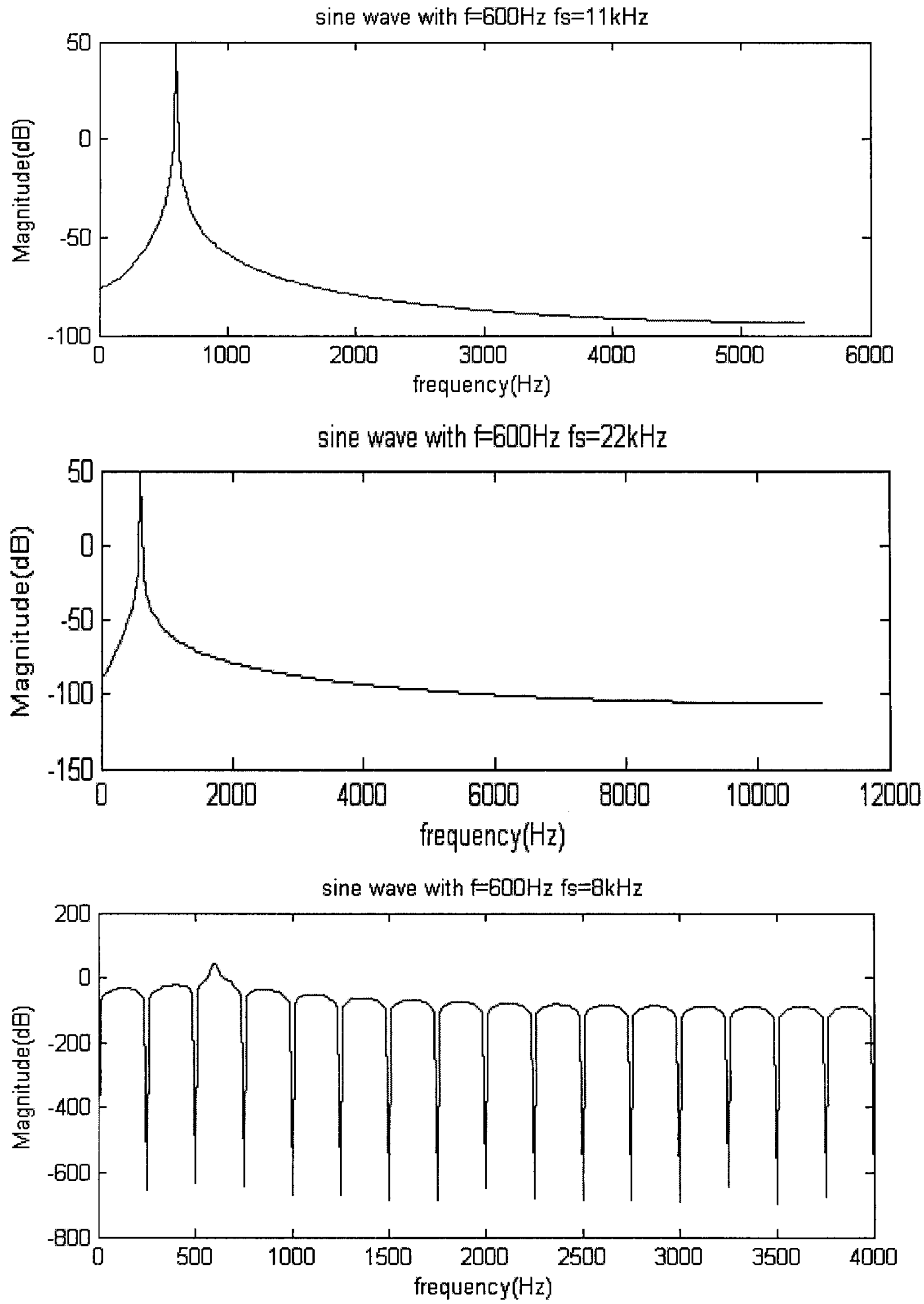

Figure 4.5 Frequency response of Sinusoidal noise with f=600Hz

4-2.4.3 White Noise Signal and Colored Noise Signal

White noise is defined as an uncorrelated noise process with equal power at all frequencies (Figure 4.6). A pure white noise is a theoretical concept, since it would need to have infinite power to cover an infinite range of frequencies. A more practical concept is band-limited white noise, defined as a noise with a flat spectrum in a limited bandwidth.

The colored noise refers to any broadband noise with a non-white spectrum. A white noise passing through a channel is "colored" by the shape of the channel spectrum. In this thesis the colored noise is generated by passing the white noise through an 11-order lowpass FIR filter with cutoff frequency f_c=2200 Hz. The frequency response of white noise and colored noise is shown in Figure 4.6; here the sampling frequency is 11 kHz.

Table 4-2 Descriptions of Reference Signals

Reference Signal	Description
1	One-frequency sine wave, as described in 4-2.4.2
2	White noise signal as described in 4-2.4.3
3	Colored noise signal as described in 4-2.4.3

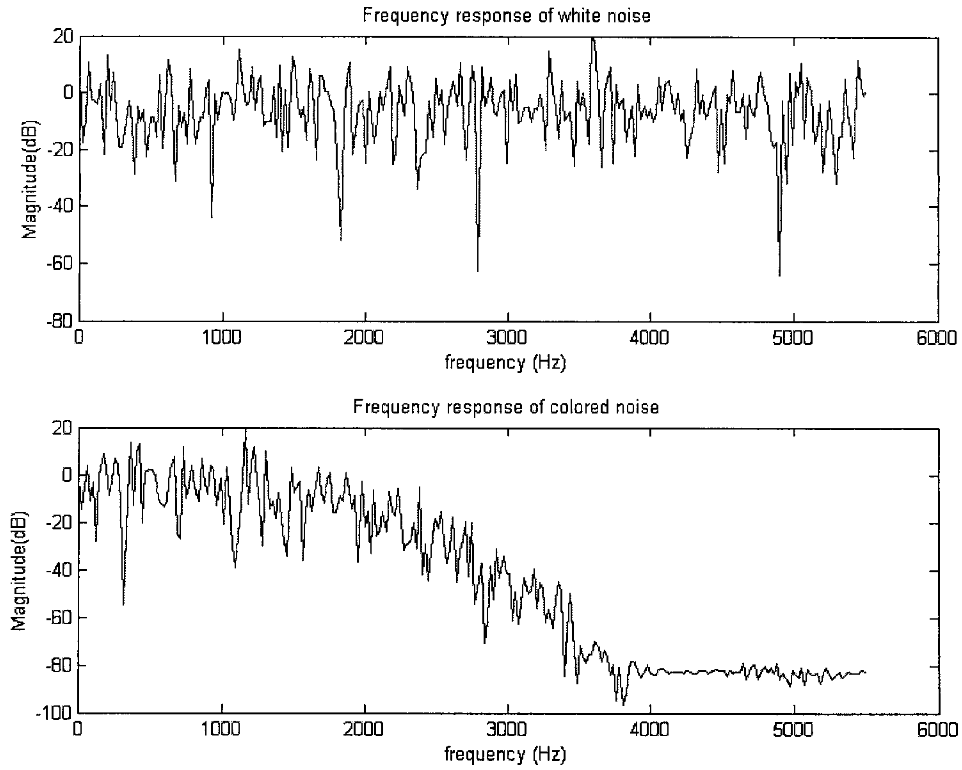

Figure 4.6 Frequency responses of White Noise and Colored Noise

4-2.4.4 Generation of noise with the desired SNR

Multiplying a factor that can control the input SNR level generates the magnitudes of the noise signals used in this thesis.

The noise signal input $x(n)$ is calculated by,

$$x(n)= Ax(n) \tag{4.19}$$

where A is a factor that can control the input SNR level, as defined by

$$A = \sqrt{\frac{\sum_{n=1}^{n=N} s^2(n)}{10^{\frac{ISNR\_Input}{10}}}} \tag{4.20}$$

where *SNR_Input* is the input SNR level in decibel (dB) and N is the total number of samples in either noise-free speech signal or noise signal.

4-2.5 Simulations

All simulations were carried out with respect to Figure 4.1 using Matlab©. The objective is to obtain an optimum quality replica speech signal from a noisy speech signal and a reference noise signal with minimal distortion. Three types of noise signal including sinusoidal noise, white noise and colored noise are used to compare the performance of the ANC. The noise component, which was a delay version of the noise source, was added to the speech signal to make the noise-corrupted signal. For S2.wave speech signal, the sampling frequency was 11 KHz; other parameters such as N, L, μ, α are shown in Table 2. For S1.wave and S3.wave the samples are different which are shown in Table 4-1.

Table 4-3 Parameters for Noise canceller

N	110033
L	8
μ	0.01
α	0.005

4-2.5.1 Removing Sinusoidal Interference from Speech Signal

Speech signal S2.wave is loaded in from a wave file and the signal is shown in Figure 4.3. A sinusoidal signal sin ($2\pi n f/f_s$) where f =600Hz is used as the noise.

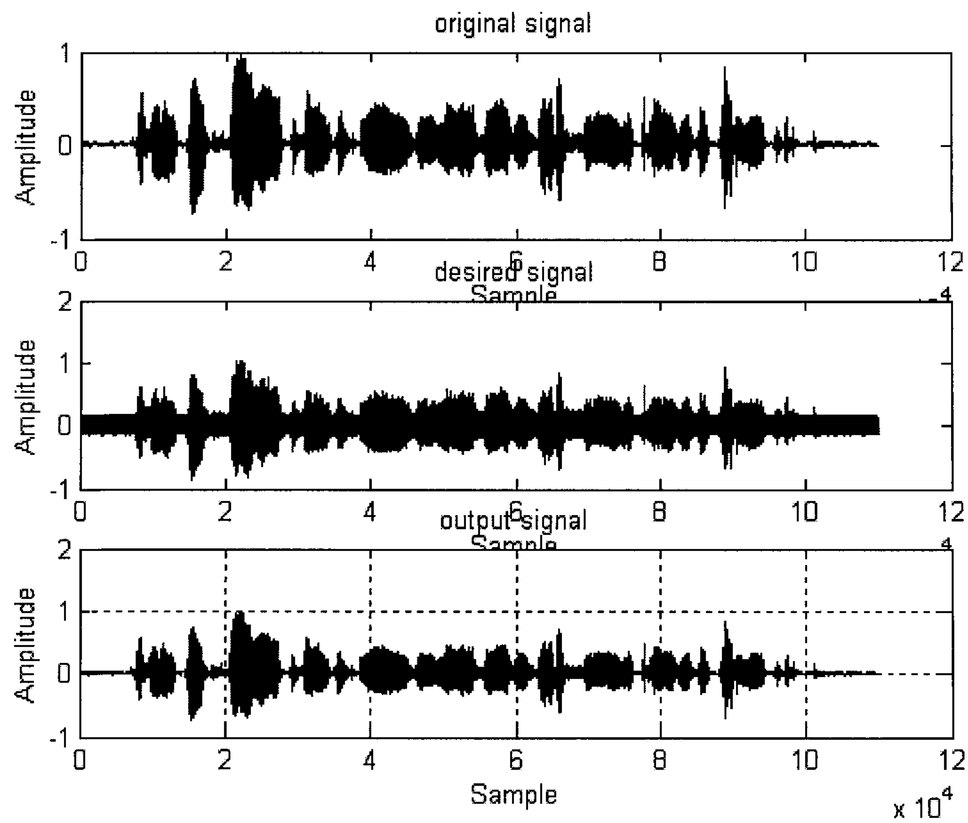

Figure 4.7 Original, desired and output signal with sine noise

4-2.5.2 Removing White Noise from Speech Signal

The speech signal S2.wave is once again read into the workspace and white noise is added to it.

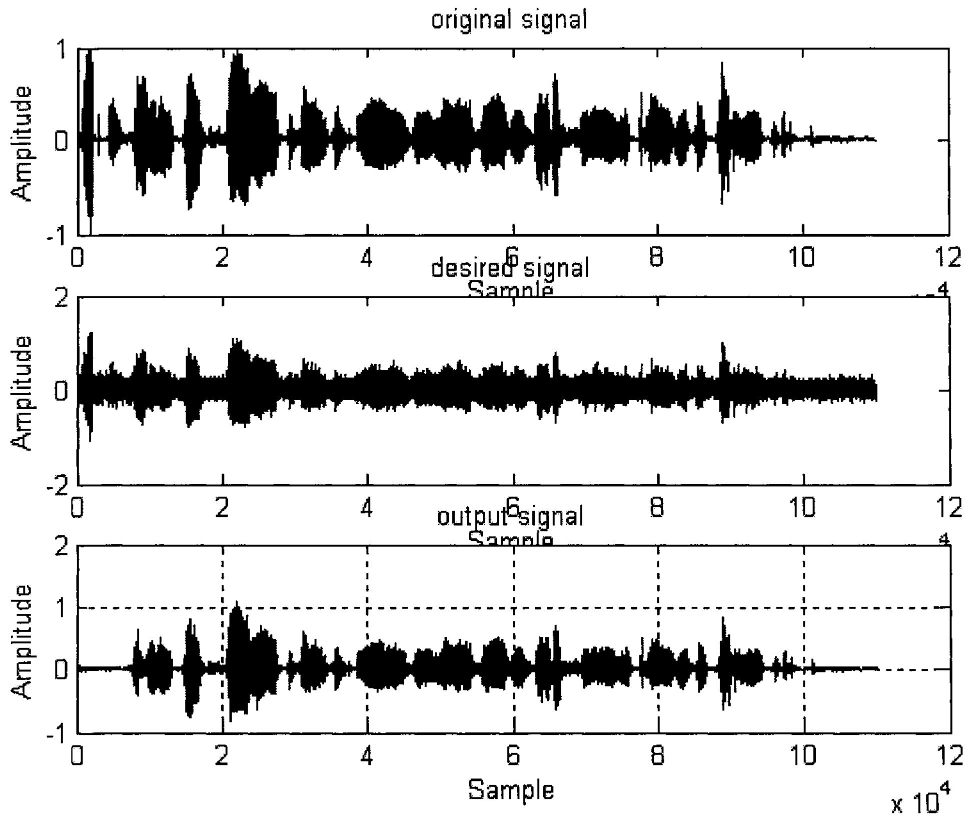

Figure 4.8 Original, desired and output signal with white noise

4-2.5.3 Removing Colored Noise from Speech Signal

Again the speech signal S2.wave is read into the workspace and colored noise is added to it.

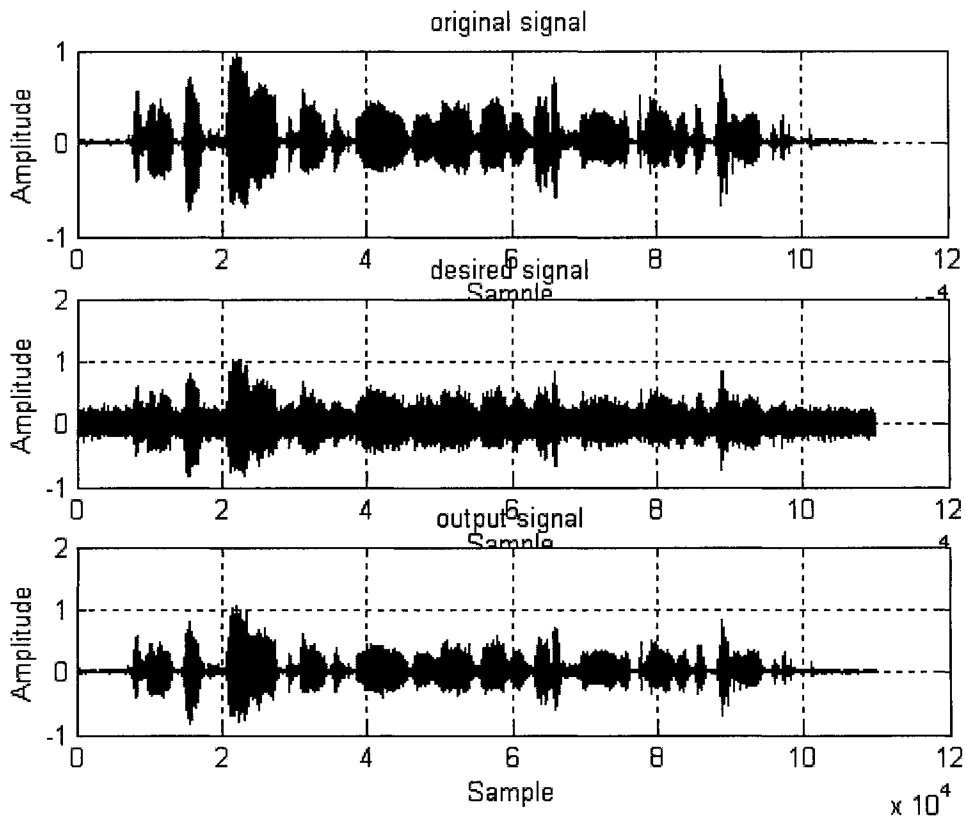

Figure 4.9 Original, desired and output signal with colored noise

4-2.6 Analysis

4-2.6.1 Basic Characteristics

Figs. 4.7-4.9 illustrate the original speech, the noise-corrupted speech (desired signal), and the noise-cancelled speech (output signal), respectively; when the noise is sinusoidal noise, white noise and colored noise respectively. The SNR in the primary signal was around 0dB. The adaptive FIR filter successfully cancels the noise.

Figs. 4.10-4.11 show the learning curves with different values of SNR and with the three types of noise signals.

Since sinusoidal interference is the simplest noise signal and as such, is the easiest to remove. And only a 2nd order adaptive filter was all that was needed to retrieve the original signal from the noisy signal. This shows that it is not the complexity of the speech signal that requires a high-order adaptive filter – it is the complexity of the noise.

White noise is the most difficult noise to fully remove since the adaptive filter potentially has to remove frequencies from 0 to the sampling frequency.

In most cases it can be attenuated to an acceptable minimum with a 6th order filter. The system was tested up to 60th order; in this case the white noise was removed from speech. From 6th order to 60th there was very little difference in speech quality.

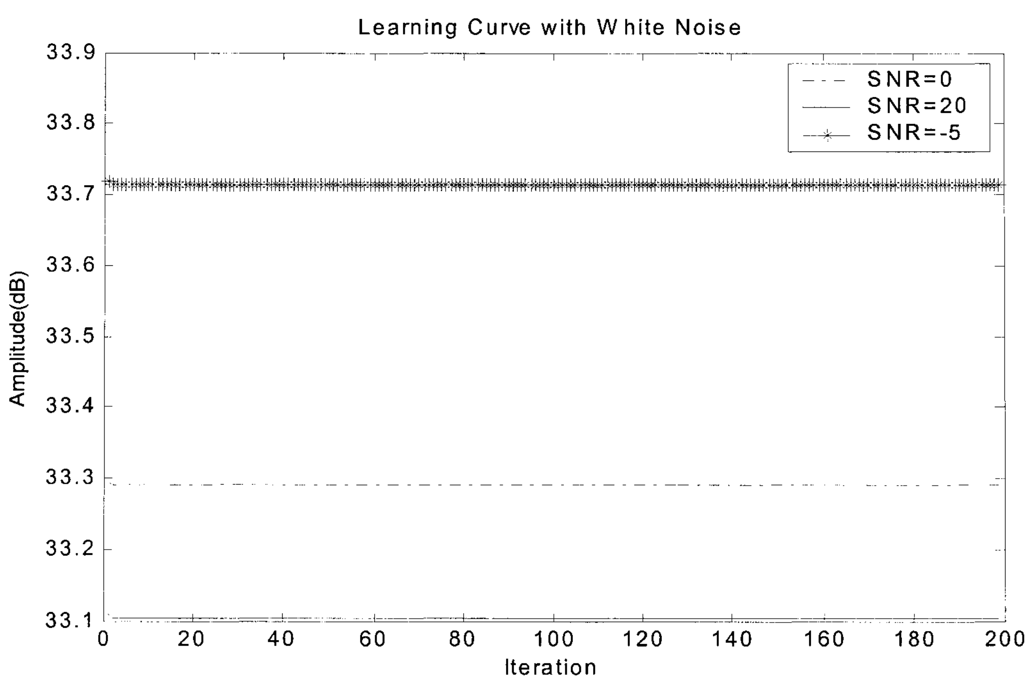

Figure 4.10 Learning curves with different SNR

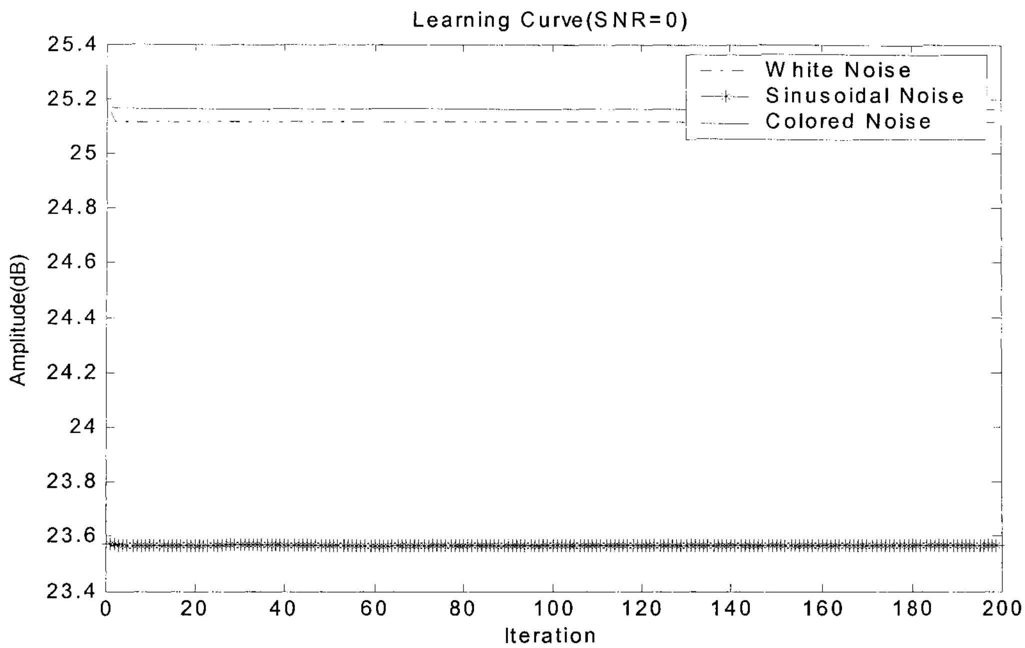

Figure 4.11 Learning curves with different types of noises

4-2.6.2 Robustness against Different SNRs

To demonstrate robustness of the adaptive filter, three different SNR values of the input signal were evaluated. These evaluations were carried out using the same filter order. Fig. 4.12 illustrates the SNR improvement in three cases where original SNR was set to 0, -5, and 10 dB when S3.wave is used as speech signal. With sinusoidal noise, the average improvement is about 24 dB, with white and colored noise the average improvement is about 16 dB. We can see that the performance of the adaptive filter does not change for different SNRs.

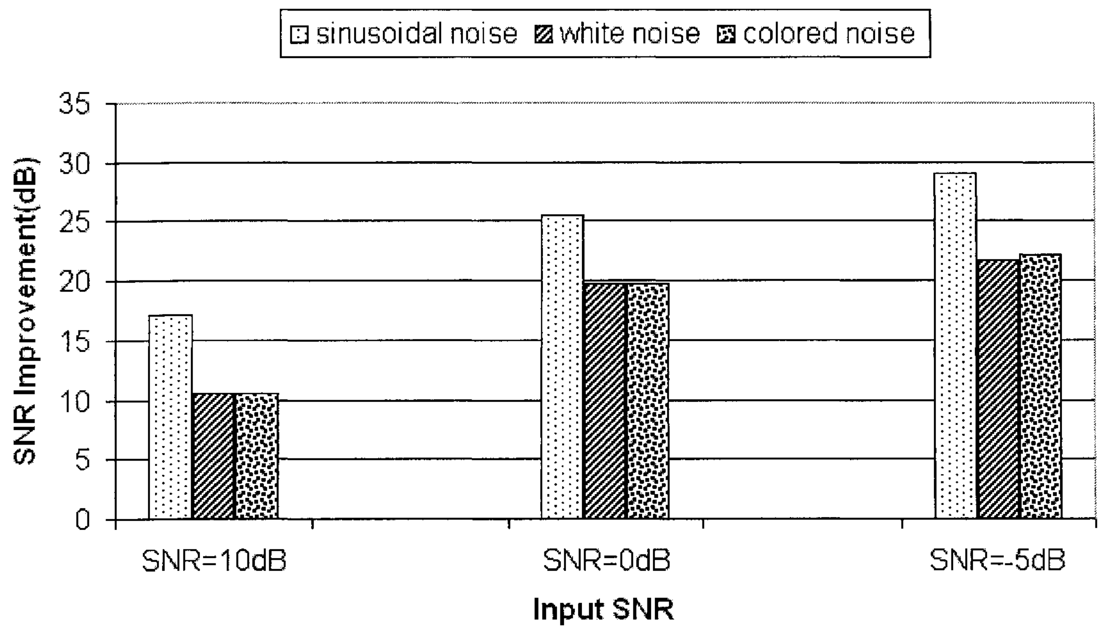

Figure 4.12 SNR improvements with different input SNR

The comparison of output SNR using different noise-free speech signals and reference signals when input SNR=10dB is shown in Figure 4-13.

When the speech signal is S3.wav and reference signal is sine noise, the output SNR is about 27 dB, which is the maximum value among all different input speech signals with different noise signals. While when the speech signal is S1.wav and reference signal is sine noise, the SNR improvement is the minimum value, about 13 dB.

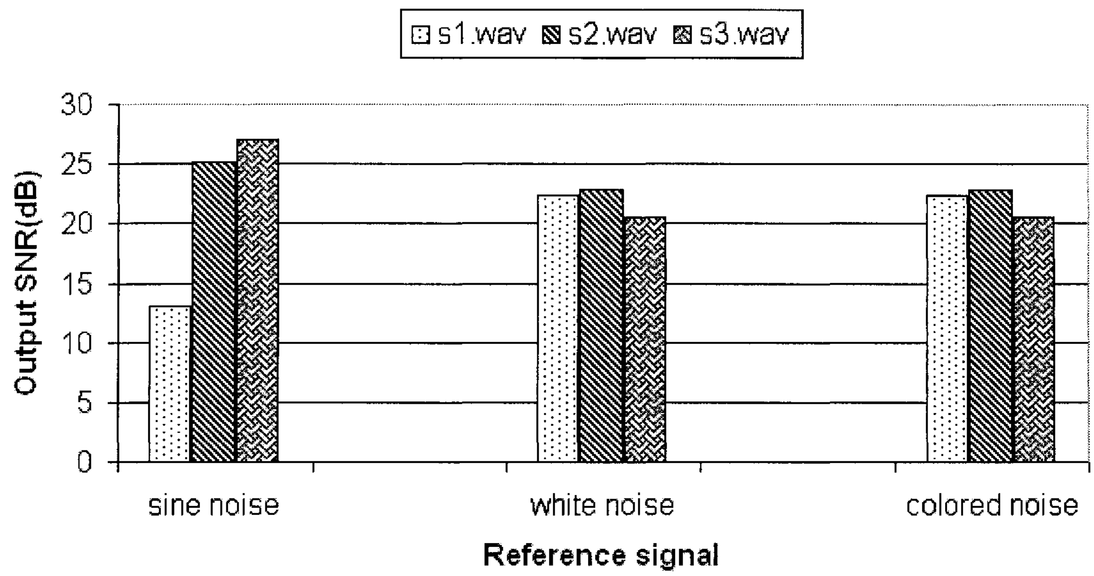

Figure 4.13 Output SNR with different speech signals and reference signals

4-3 FIR Adaptive Echo Canceller

4-3.1 Adaptive Echo Cancellation

4-3.1.1 Origins of Echo

Echo is a phenomenon in which a delayed and distorted version of an original sound or electrical signal is reflected back to the source.

In telephone communication, there are two main types of echo: network (or line) and acoustic echoes. Network echo will occur when a communication is just between two fixed handset telephones. If a communication is between one or more hand-free telephones (or speaker phones), the human communicator is separated from the microphone, then acoustic feedback paths are set up between the telephone's loudspeaker and microphone at each end. In this communication system, when a signal is received, it is output through the loudspeaker into an acoustic environment. This signal is reverberated within the environment and returned to the system via microphone input. These multiply reverberated signals contain time-delayed version of the original signal, which are then returned to the original sender as annoying acoustic echoes. Acoustic echo occurs whenever there is an acoustic coupling between a loudspeaker and a microphone. The problem is schematically shown in Figure 4.14. The loudspeaker signal, coming from a far-end speaker, propagated through the room and feeds back to the microphone as an echo.

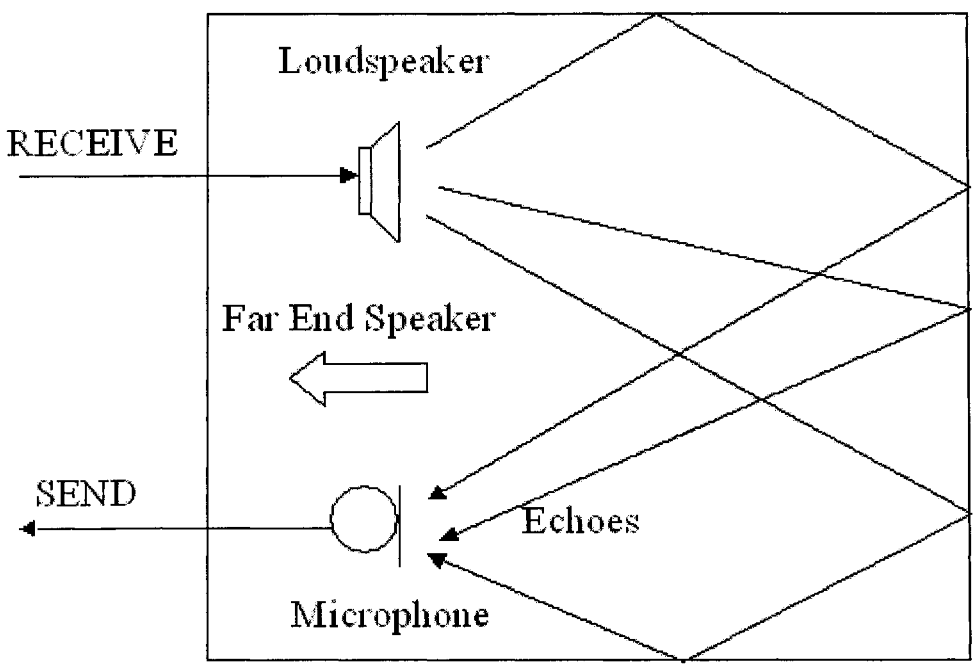

Figure 4.14 Generation of acoustic echoes

4-3.1.2 Description of Adaptive Echo Canceller (AEC)

Echo cancellation was developed in the early 1960s at AT&T Bell Labs by Kelly, Logan, and Sondhi [62, 63] and later by COMSAT TeleSystems. The original purpose of the invention was to cancel electric echoes on telephone networks, but the same method can be applied to acoustic echoes. The first echo cancellation systems were experimentally implemented across satellite communication networks to demonstrate network performance for long-distance calls.

In this section, we focus on single-channel AEC, with one loudspeaker and one microphone. Figure 4.15 illustrates the general echo canceller block diagram. The speech signal from the far-end speaker is input to the near-end device and to the echo canceller. The echo canceller monitors the signal from near-end to far-end and attempts to model and estimate the impulse response of the echo path and generates a replica of the echo of far-end speaker. Following that, this replica is used to subtract and cancel out the echo of speaker from the received signal. The objective is to eliminate the sound (through loudspeaker) from the far end speaker being transmitted again to him or her through the microphone.

Referring to Figure 4.15, four signals are defined:

(1) $x(n)$: input signal (from the far end speaker) to the near end speaker
(2) $d(n)$: desired signal (echoed signal)
(3) y(n): replica of the echo (generated by the adaptive filter that models the transfer function of the room)
(4) e(n): the difference between the desired signal d(n) and estimated echo y(n) (e(n)=d(n) – y(n))

The aim of the echo canceller is to cancel the desired signal $d(n)$ (echoes) and try to keep the error signal $e(n)$ to the best possible minimum value. From Figure 4.14, it is noted that the error signal $e(n)$ is fed back to the adaptive filter, this feedback is used by adaptive filter to correct its estimation process.

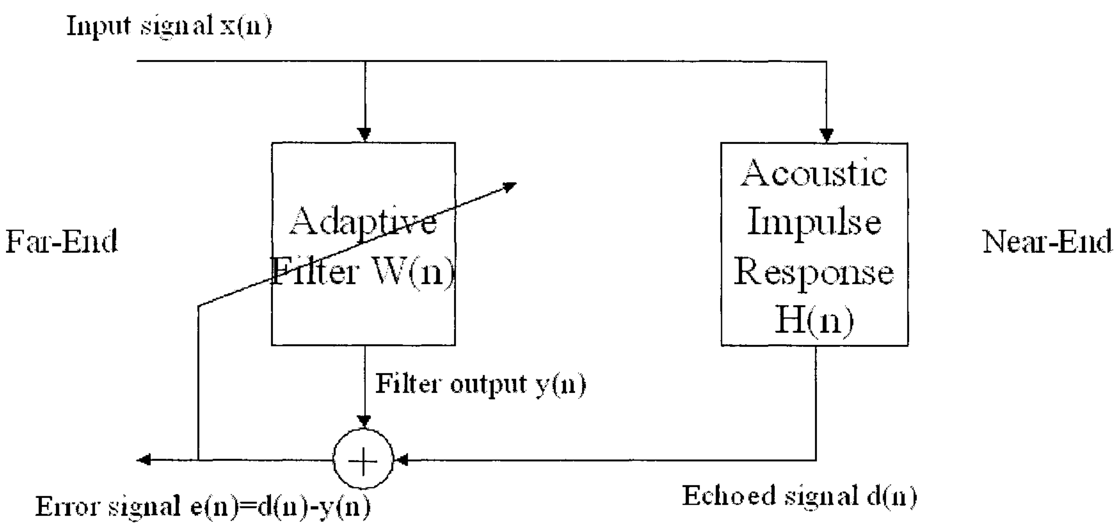

Figure 4.15 Block diagram of adaptive echo canceller

4-3.2 Simulations

4-3.2.1 Introduction

All simulations were carried out with respect to the application of acoustic echo cancellation depicted in Figure 4.16 using Matlab©. The objective is to accurately estimate the echo path characteristic and rapidly adapt to its variation using NLMS algorithm such that the estimation error e(n) is minimum. The near-end room impulse response is modeled using a 128^{th} order FIR filter. The impulse response is shown in Figure 4.17. The typical shape of the impulse response curves is the following: They initially have delay, followed by a response with rapid time variation, and a tail that is oscillatory and slowly decaying toward zero. A real speech signal shown in Figure 4.2 to Figure 4.4 is used as the far-end input. The entire adaptive filter coefficients are initialized to zeros. We assume far-end only talk (with only one far-end talker at any time) for our simulations, since the adaptive filters are usually adapted only under this condition.

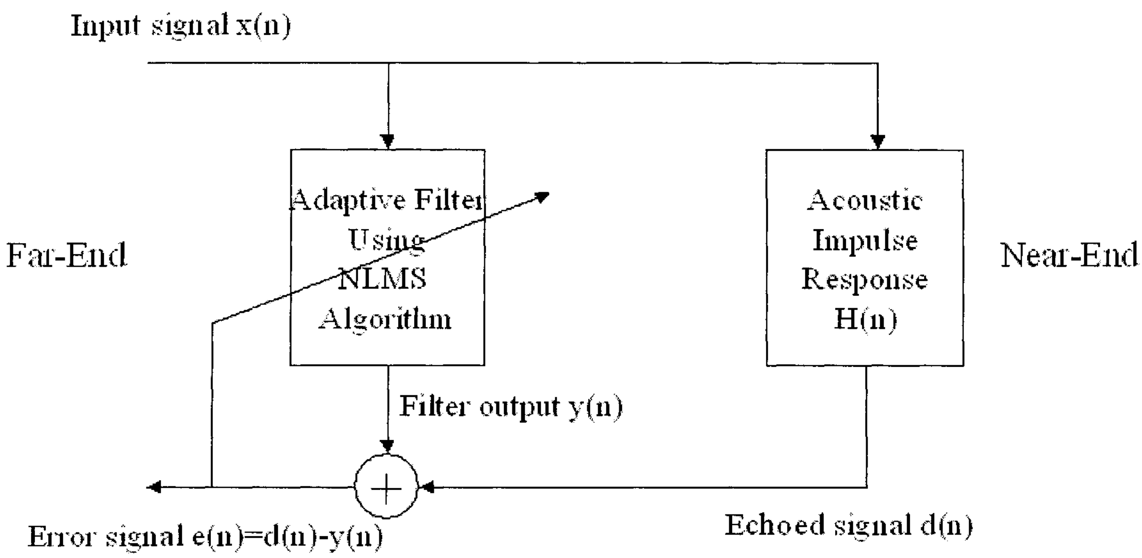

Figure 4.16 Acoustic echo cancellation using NLMS algorithm

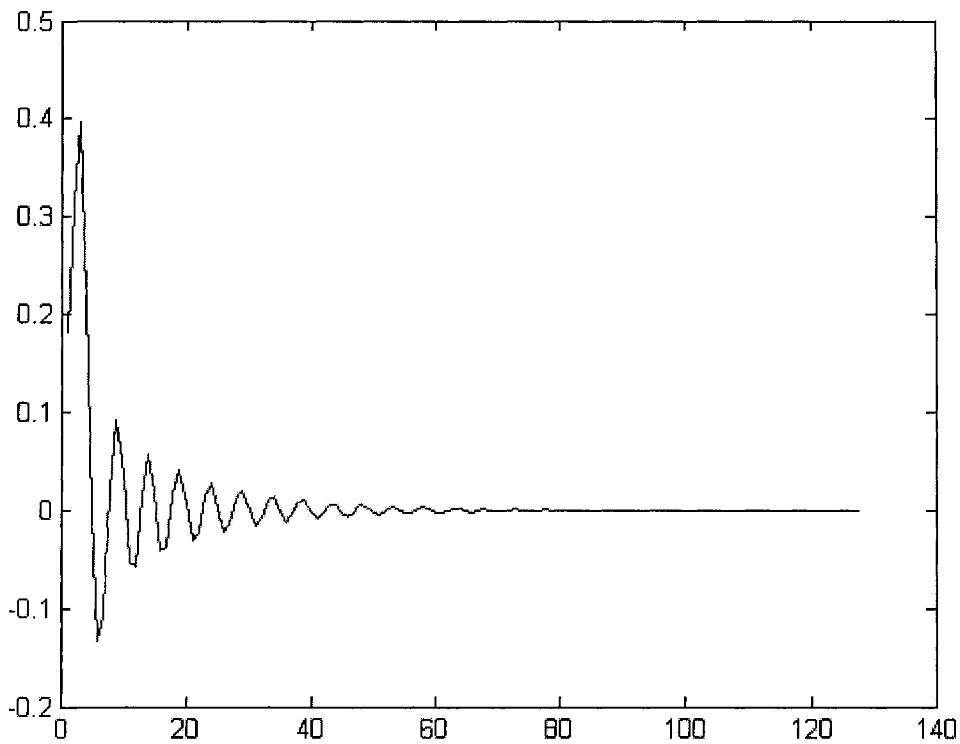

Figure 4.17 Impulse response H(n) of the near-end room

4-3.2.2 Simulations

Simulations involving speech input consisted of 12,000 sample points and echo path was assumed to have known impulse response, h(n) of 128 points long. The filter length was taken to be128 taps. The step size constant μ was set to be 0.01 for all the simulations and it was assumed to be noise free. Also, the near end speaker was assumed to be silent.

4-3.3 Analysis

4-3.3.1 Performance Measures

As part of the analysis of the NLMS algorithm, some performance measures need to be defined first.

(1) The output estimation error (also known as the learning curve) is defined as

$$\text{Output Estimation Error} = 20\log_{10}(|e(n)|) \tag{4.21}$$

(2) Weight estimation error is given as

$$\text{Weight Estimation Error} = \frac{\left\| h(n) - w(n) \right\|^2}{\left\| h(n) \right\|^2} \tag{4.22}$$

where h(n) is the actual impulse response of the system, w(n) is the estimated tap-weight vector and || || denotes the norm of 2.

Figure 4.18 shows the learning curve and the weight estimation error with speech input. It is observed that as the adaptive filter estimations the weight vector to be as close to the actual impulse response h(n), the output estimation error reduces. And also the value of step size parameter affects convergence speed (see Figure 4.19).

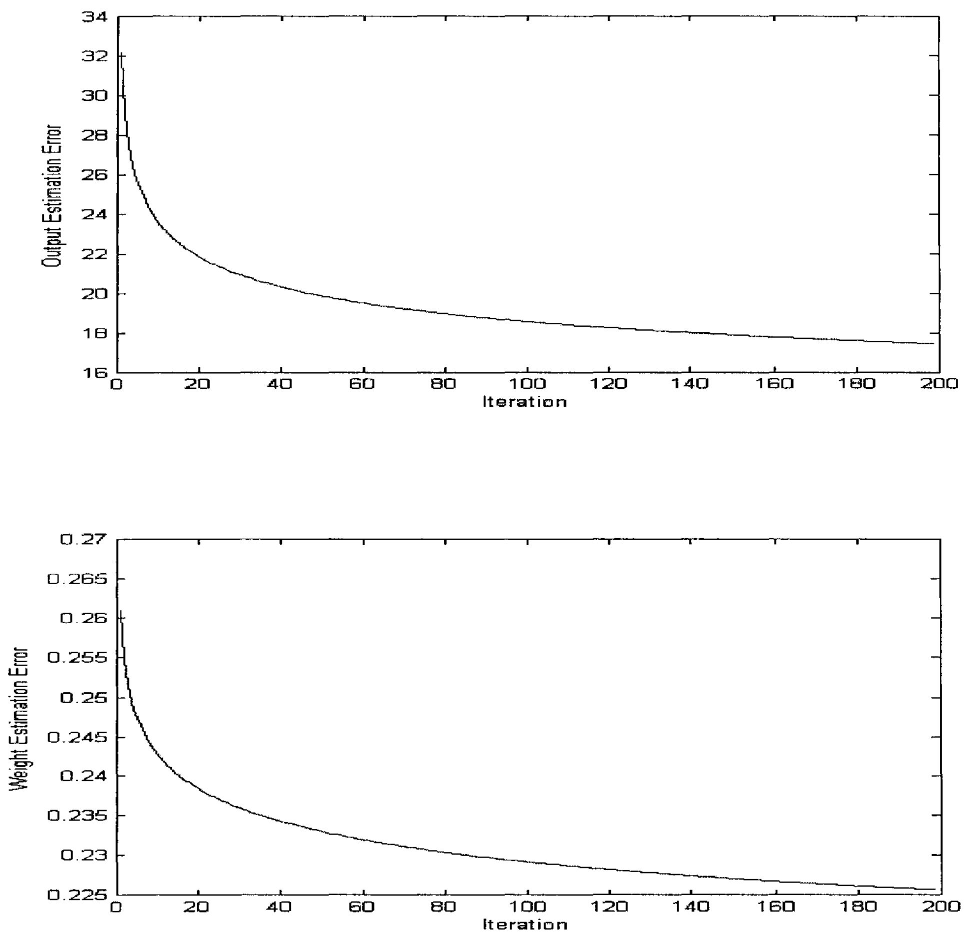

Figure 4.18 Learning curve and weight estimation error

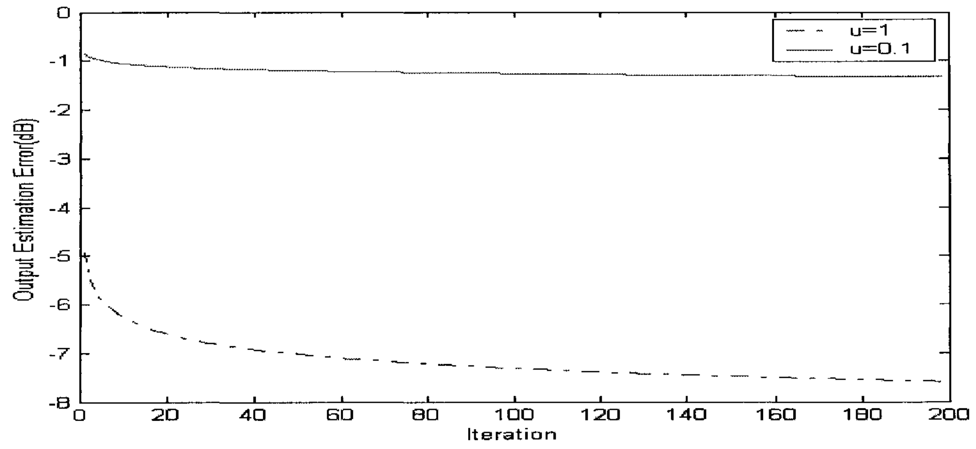

Figure 4.19 Learning curves with different step size

An interesting point to note is that convergence speed depends on the length of the filter. This is illustrated in Figure 4.20.

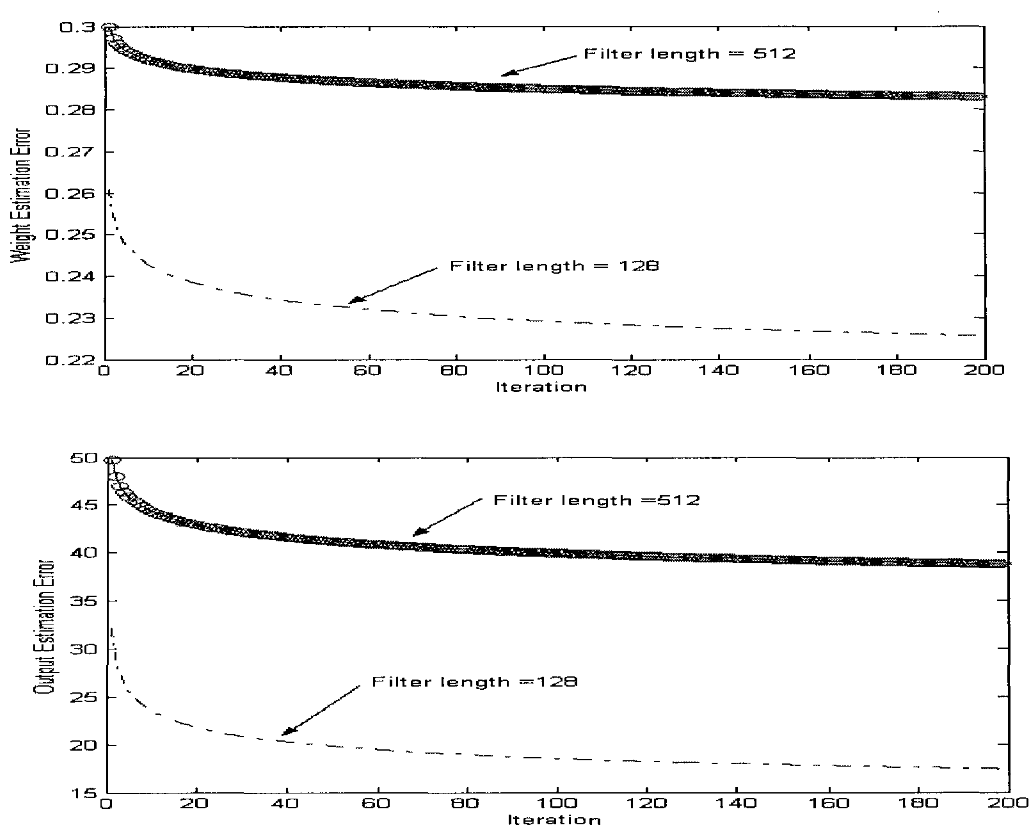

Figure 4.20 Learning curves for different filter length

(3) Echo return loss enhancement (ERLE) is defined as

$$\text{ERLE} = 10\log_{10}\frac{\hat{E}[d^2(n)]}{\hat{E}[e^2(n)]} \tag{4.23}$$

where $\hat{E}$ denotes the estimated expected value by means of moving averages. Here ERLE is defined as the ratio of energy in the original echo d(n) to the energy in the residual echo. In other words, ERLE is a measure of how much echo is attenuated in decibel (dB). By computing ERLE, the convergence rate can be studied and analyzed. In this chapter the ERLE is computed using a 128-point moving average of the instantaneous squared amplitudes. The ERLE for speech input is shown in Figure 4.21 and peaks represent the amount of echo being suppressed. Usually 20dB or more ERLE is expected for effective echo cancellation.

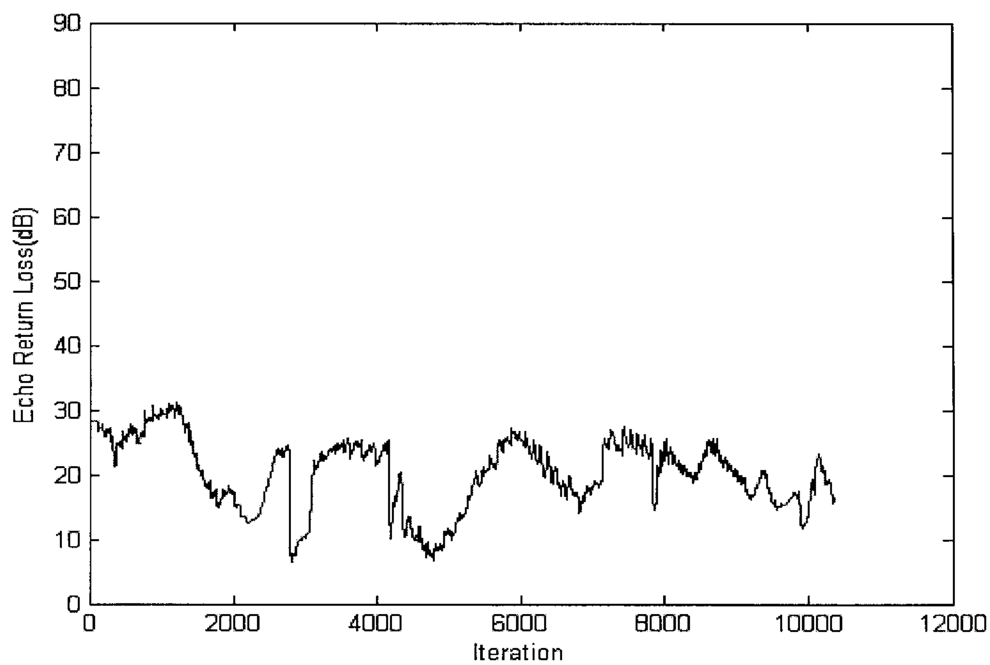

Figure 4.21 The ERLE for speech input (N=16)

Chapter 5

IIR Adaptive Noise and Echo Cancellation

5-1 Introduction

Earlier we discussed the adaptive FIR filters in the previous chapter, which are non-recursive that the filter output is computed based on finite number of input samples. Adaptive FIR filter have developed to a maturity of practical implementation. A major drawback of the adaptive FIR filters is that certain applications would require a very large number of coefficient parameters to achieve good performance, thus increasing computational costs. This becomes evident when the system to be modeled or identified is represented as a pole-zero model.

On the other hand, adaptive filters based upon the infinite impulse response (IIR) structure have the advantage of reducing the computational cost. Widely researches have been explored on the application of adaptive IIR filers. It is expected that these adaptive IIR filters will efficiently model the systems whose responses often contain poles and zeros and improve the performance of their counterparts in many areas, for example, in echo cancellation. Although adaptive IIR filters require fewer coefficients to be estimated, they have two main problems in the realization:

1. IIR filter may become unstable during adaptation since their poles may move out of the unit circle. To deal this problem, some filters employ stability monitoring by checking the location of the instantaneous poles of the system and projecting the coefficients back to a region for which the instantaneous poles are within the unit circle. Unfortunately, time-varying filters may be unstable even when the

instantaneous poles are within the unit circle [26]. But this potential problem is often ignored in practice and is usually not observed in computer simulations.

2. The performance function for an IIR filter can be nonconvex, which implies the existence of multiple local minima points. Researches investigated on this problem show that there are no local mimima if the following conditions exist: (1) the adaptive filter transfer function has sufficient order (poles and zeros) to exactly model the unknown system (the order of the adaptive filter can be greater than that of the unknown system), (2) the number of recursive taps is smaller than the number of transversal taps.

5-2 Adaptive IIR Filtering

5-2.1 Introduction

Figure 5.1 shows the basic block diagram of an IIR adaptive filter. At each iteration, a sampled input signal x(n) is passed through an adaptive IIR filter to generate the output signal y(n). This output signal is compared to a desired signal d(n) to generate the error signal e(n). Finally, an adaptive algorithm uses this error signal to adjust the adaptive filter coefficients in order to minimize a given objective function.

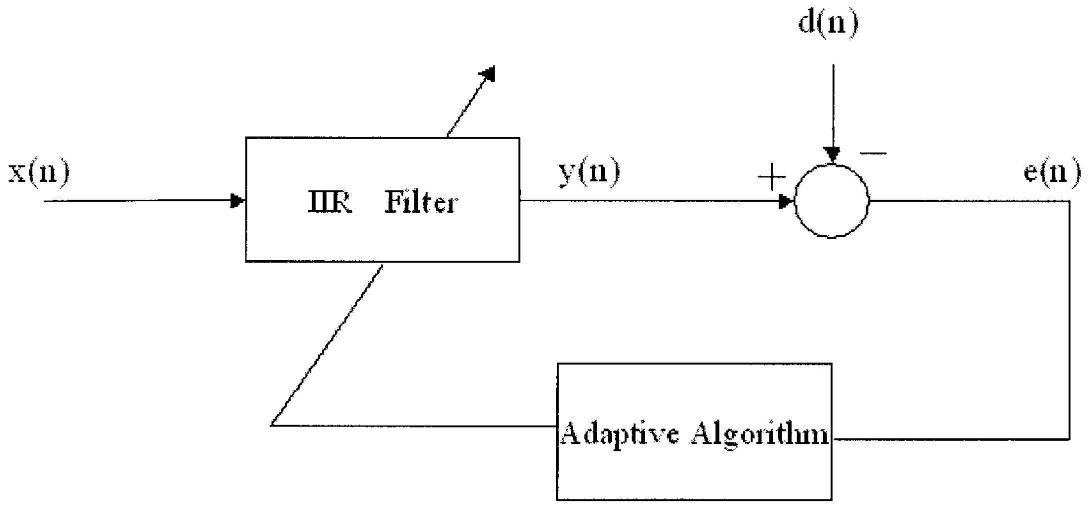

Figure 5.1 Adaptive IIR filter model

5-2.2 The Output Error Method

The output error method results when a direct form IIR filter realization is used in Wiener filter to develop adaptation algorithms. Figure 5.2 depicts the block diagram of output error method.

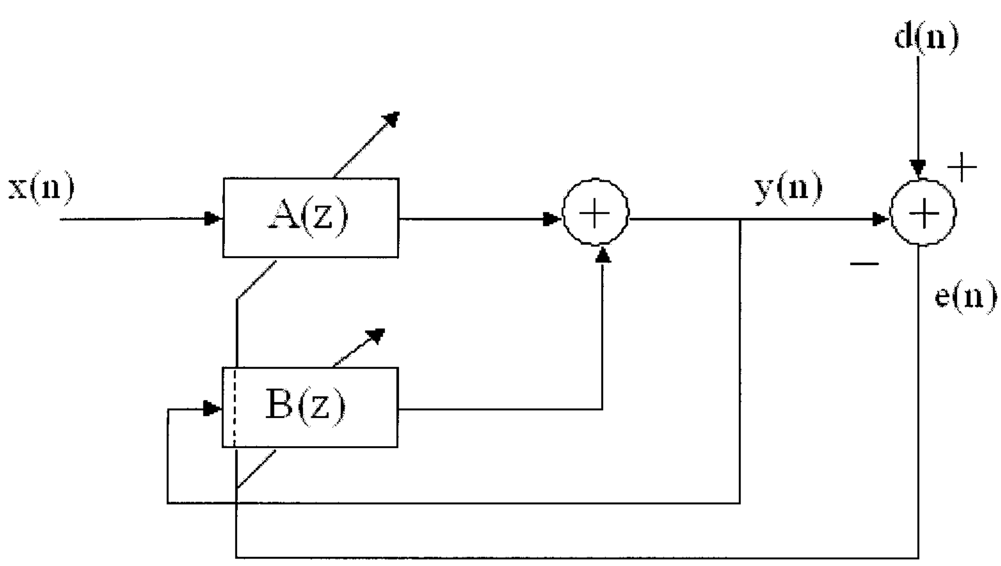

Figure 5.2 Block diagram of output error method

In the following we will present the formulation of the IIR-LMS algorithm. The IIR filter kernel in direct form is constructed as

$$y(n) = \sum_{i=0}^{N} b_i(n)x(n-i) + \sum_{j=1}^{M} a_j(n)y(n-j) \tag{5.1}$$

where $a_i(n)$ and $b_j(n)$ are adjustable coefficients of the filter. Equation (5.1) can also be written equivalently by the transfer function

$$H(z) = \frac{B(z)}{1-A(z)} \tag{5.2}$$

where the polynomials

$$A(z) = \sum_{i=0}^{N} b_i z^{-i} \tag{5.3}$$

and

$$B(z) = \sum_{j=1}^{M} a_j z^{-j} \tag{5.4}$$

are obtained by minimizing the output error, $e(n)$, in the mean-square sense.

The instantaneous cost function is defined as

$$J(n) = e^2(n) \tag{5.5}$$

and

$$e(n) = d(n) - y(n) \tag{5.6}$$

Let the weight vector $\mathbf{w}(n)$, $\mathbf{x}(n)$ be defined as

$$\mathbf{w}(n) = [b_0,\ \ldots,\ b_N,\ a_1,\ \ldots,\ a_M]^T \tag{5.7}$$

$$\mathbf{x}(n) = [x(n),\ \ldots,\ x(n-N),\ y(n-1),\ \ldots,\ y(n-M)]^T \tag{5.8}$$

and $d(n)$ is the desired output. The output $y(n)$ is

$$y(n) = \mathbf{w}^T(n)\ \mathbf{x}(n) \tag{5.9}$$

The error e(n) can be written as

$$e(n) = d(n) - y(n) = d(n) - \mathbf{w}^T(n)\ \mathbf{x}(n) \tag{5.10}$$

so the gradient is

$$\nabla_{\mathrm{w}} = \frac{\partial e^2}{\partial w} = 2e\frac{\partial e}{\partial w}$$

$$=2e(n)[\ \frac{\partial e(n)}{\partial b_0},\cdots,\frac{\partial e(n)}{\partial b_N},\frac{\partial e(n)}{\partial a_1},\cdots,\frac{\partial e(n)}{\partial a_M}\ ]^{\mathrm{T}} \tag{5.11}$$

$$=-2e(n)[\ \frac{\partial y(n)}{\partial b_0},\cdots,\frac{\partial y(n)}{\partial b_N},\frac{\partial y(n)}{\partial a_1},\cdots,\frac{\partial y(n)}{\partial a_M}\ ]^{\mathrm{T}} \tag{5.12}$$

let us define

$$\nabla_w y(n) = [\ \frac{\partial y(n)}{\partial b_0},\cdots,\frac{\partial y(n)}{\partial b_N},\frac{\partial y(n)}{\partial a_1},\cdots,\frac{\partial y(n)}{\partial a_M}\ ]^{\mathrm{T}} \tag{5.13}$$

From Equation (5.1), obtain

$$\nabla_w y(n) = [x(n),\ \ldots,\ x(n-N),\ y(n-1),\ \ldots,\ y(n-M)]^{\mathrm{T}}$$

$$+ [\sum_{j=1}^{M} b_j \frac{\partial y(n-j)}{\partial a_0},\cdots,\sum_{j=1}^{M} b_j \frac{\partial y(n-j)}{\partial a_N},\sum_{j=1}^{M} b_j \frac{\partial y(n-j)}{\partial b_1},\cdots,\sum_{j=1}^{M} b_j \frac{\partial y(n-j)}{\partial b_M}]^T \tag{5.14}$$

$$= X(n) + \sum_{j=1}^{M} b_j \nabla_w y(n-j) \tag{5.15}$$

where the gradient estimate is given by

$$\nabla_{\mathrm{w}} = -\ 2e(n)\ \nabla_w y(n) \tag{5.16}$$

Based on the gradient descent algorithm, the coefficient update is

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu\nabla_{\mathrm{w}} \tag{5.17}$$

where $\mathbf{w}(n)$ denotes the old weight vector of the filter at iteration n and $\mathbf{w}(n+1)$ denotes its updated weight vector at iteration $n+1$.

Therefore, in IIR- LMS, the coefficient update becomes

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\,\mu[\,d(n) - y(n)]\nabla_{\mathrm{w}}y(n) \tag{5.18}$$

5-2.3 Adaptive IIR Normalized LMS algorithm

The output error method based on LMS algorithm may have the local minimum problem when the error surface is multimodal. Several methods have been proposed for the global optimization of the adaptive IIR filtering [16, 22, 23].

Since the LMS algorithm uses the instantaneous (stochastic) gradient instead of the expected value of the gradient, error occurs in estimating the gradient. This gradient estimation error, when properly normalized, can be used to act as the perturbing noise. Consequently the normalized LMS (NLMS) algorithm can be used for global IIR filter optimization. In this thesis we use NLMS algorithm as the adaptation algorithm for IIR filter.

In the following we will review the NLMS algorithm [2], and show that the NLMS algorithm has global optimization behavior.

Consider the problem of minimizing the squared Euclidean norm of the weight change,

$$\delta\mathbf{w}(n+1) = \mathbf{w}(n+1) - \mathbf{w}(n) \tag{5.19}$$

subject to the constraint

$$\mathbf{w}^{T}(n+1)\,\mathbf{x}(n) = d(n) \tag{5.20}$$

To solve this constrained optimization problem, we use the method of Lagrange multipliers. According to this method, the cost function for the problem consists of two parts, given on the right-hand side of the equation

$$J(n) = \|\,\delta\mathbf{w}(n+1)\|^2 + \mathrm{Re}\,[\lambda^*(d(n) - \mathbf{w}^T(n+1)\mathbf{x}\,(n))] \tag{5.21}$$

The square norm of $\delta\mathbf{w}(n+1)$ is

$$\begin{aligned}\|\,\delta\mathbf{w}(n+1)\|^2 &= \delta\mathbf{w}^{T}(n+1)\;\delta\mathbf{w}(n+1)\\ &= [\mathbf{w}(n+1) - \mathbf{w}(n)\,]^{\mathrm{T}}\,[\mathbf{w}(n+1) - \mathbf{w}(n)\,]\\ &= \sum_{k=0}^{N} |\,w_k(n+1) - w_k(n)\,|^2\end{aligned} \tag{5.22}$$

The constraint of Equation (5.20) can be represented as

$$\sum_{k=0}^{N} w_k(n+1)x(n) = d(n) \tag{5.23}$$

The cost function $J(n)$ is formulated by combining Equations (5.22) and (5.23) as

$$J(n) = \sum_{k=0}^{N} |\,w_k(n+1) - w_k(n)\,|^2 + \lambda\,[\,d(n) - \sum_{k=0}^{N} w_k(n+1)x(n)\,] \tag{5.24}$$

where λ is a Lagrange multiplier. After differentiating the cost function $J(n)$ with respect to the parameters and setting the results to zero, we obtain

$$2[\mathbf{w}(n+1) - \mathbf{w}(n)] = \lambda^*\mathbf{x}(n) \tag{5.25}$$

Substituting this result into the constraint of Equation (5.20), we get

$$\lambda = \frac{2e(n)}{\| x(n) \|^2} \tag{5.26}$$

By substituting the above equation into Equation (5.25), we have

$$\delta \mathbf{w}(n+1) = \frac{1}{\| x(n) \|^2} e^*(n)\mathbf{x}(n) \tag{5.27}$$

By introducing a positive real scaling factor denoted by $\widetilde{\mu}$, Equation (5.27) is redefined as

$$\delta \mathbf{w}(n+1) = \frac{\widetilde{\mu}}{\| x(n) \|^2} e^*(n)\mathbf{x}(n) \tag{5.28}$$

Equivalently, we write as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\widetilde{\mu}}{\| x(n) \|^2} e^*(n)\mathbf{x}(n) \tag{5.29}$$

This is the so-called NLMS algorithm. To avoid the problem that Equation (5.29) may be divided by a small value of the squared norm $\|x(n)\|^2$, we modify Equation (5.29) slightly to produce

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\widetilde{\mu}}{\delta + \| x(n) \|^2} e^*(n)\,\mathbf{x}(n) \tag{5.30}$$

where $\delta > 0$.

5-2.4 The Global Optimization Behavior of NLMS Algorithm

In this section we follow the lines of Widrow et al. [1] and assume that the NLMS algorithm will converge to the vicinity of a steady-state point.
The MSE objective function can be described as

$$\xi(w) = \frac{1}{2}E\{e^2(w)\} = \frac{1}{2}E\{[d(n) - y(n)]^2\} \tag{5.31}$$

Where E is the statistical expectation.

The output signal of the adaptive IIR filters, represented a direct-form realization of a linear system, is

$$\begin{aligned} y(n) &= b_0 x(n) + \dots + b_{n-N+1}x(n-N+1) \\ &\quad + a_1 y(n-1) + \dots + a_{n-M+1}y(n-M+1) \end{aligned} \tag{5.32}$$

which can be rewritten as

$$y(n) = \mathbf{w}^T(n)\Phi(n) \tag{5.33}$$

where $\mathbf{w}(n)$ is the coefficient vector and $\Phi(n)$ is the input vector.

$$\mathbf{w}(n) = [b_0(n), \dots, b_{N-1}(n), a_1(n), \dots, a_{M-1}(n)]^T \tag{5.34}$$

$$\Phi(n) = [x(n), \dots, x(n-N+1), y(n-1), \dots, y(n-M+1)]^T \tag{5.35}$$

The MSE objective function is

$$\xi(n, w) = \frac{1}{2}E\{[d(n) - w^T(n)\phi(n)]^2\} \tag{5.36}$$

Now we use the instantaneous value as the expectation of $E\{e^2(n)\} \approx e^2(n)$ such that

$$\xi(n, w) = \frac{1}{2}e^2(n,w) = \frac{1}{2}[d(n) - w^T(n)\phi(n)]^2 \tag{5.37}$$

Estimating the gradient vector with respect to the coefficient w, we get

$$\begin{aligned} \nabla\xi(n, w) &= \nabla_w \frac{1}{2}[e^2(n,w)] = e(n,w)\nabla_w[e(n,w)] \\ &= - e(n, w)\, \nabla_w y(n) = - e(n, w)\begin{bmatrix} \dfrac{\partial e(n,w)}{\partial a_i} \\ \dfrac{\partial e(n,w)}{\partial b_i} \end{bmatrix} \end{aligned} \tag{5.38}$$

Define N(n) as a vector of the gradient estimation noise in the n^{th} iteration and $\nabla\xi(w(n))$ as the true gradient vector. Thus

$$\begin{aligned} \tilde{\nabla}\xi(w(n)) &= \nabla\xi(w(n)) + N(n) \\ N(n) &= \tilde{\nabla}\xi(w(n)) - \nabla\xi(w(n)) \end{aligned} \tag{5.39}$$

If we assume that the NLMS algorithm has converged to the vicinity of a local steady-state point w*, then $\nabla\xi(w(n))$ will be close to zero. Therefore the gradient estimation noise will be

$$N(n) = \tilde{\nabla}\xi(w(n)) = -e(n)\nabla_w y(n) \tag{5.40}$$

The covariance of the noise is given by

$$Cov[N(n)] = E[N(n)\, N^T(n)] = E[e^2(n)\nabla_w y(n)\nabla_w y^T(n)] \tag{5.41}$$

We assume that $e^2(n)$ is approximately uncorrelated with $\nabla_w y(n)$ (the same assumption as [1]), thus near the local minimum

$$Cov[N(n)] = E[e^2(n)]E[\nabla_w y(n)\ \nabla_w y^T(n)] \tag{5.42}$$

We rewrite the NLMS algorithm as

$$w(n+1) = w(n) + \frac{\mu(n)}{\| \nabla_w y(n) \|^2} \tilde{\nabla}\xi(w(n)) \tag{5.43}$$

Substituting Equation (5.39) into the above equation, we obtain

$$w(n+1) = w(n) + \frac{\mu(n)}{\| \nabla_w y(n) \|^2} (\nabla\xi(w(n)) + N(n)) \tag{5.44}$$

$$w(n+1) = w(n) + \frac{\mu(n)}{\| \nabla_w y(n) \|^2} \nabla\xi(w(n)) + \frac{\mu(n)}{\| \nabla_w y(n) \|^2} N(n) \tag{5.45}$$

where the last term is the appending perturbing noise. Its covariance, from Equation (5.42), is

$$\mathrm{cov}[\frac{N(n)}{\| \nabla_w y(n) \|^2}] = \frac{\mathrm{cov}[N(n)]}{\| \nabla_w y(n) \|^2} = \frac{E[e^2(n)]E[\nabla_w y(n) \nabla_w y^T(n)]}{\| \nabla_w y(n) \|^2}$$

$$\cong E[e^2(n)]\Lambda \tag{5.46}$$

where Λ is an unit norm matrix. Thus the NLMS algorithm near any local or global minima has the variance of the perturbing random noise determined solely by both $\mu(n)$ and $e(n)$, which is independent of the gradient. This gives NLMS chance to escape out of local minima.

5-2.5 Survey of Stability Monitoring

Stability is one of the important issues in implementing recursive digital adaptive filters. An adaptive IIR filter is said to be stable is its response to a bounded input sequence is a bounded sequence (BIBO). But ensuring the stability of the adaptive IIR filter is still an open issue and only few results available in the literature for combating this problem. Carini et al [26] presented a stability condition for direct-form recursive systems; this condition was successfully applied for designing bounded-input, bounded-output stable adaptive filters. Some algorithms employ normalized lattice structure [6], [7] which is guaranteed to be stable if the reflection coefficients are bounded by one. Lee and Mathews [24] proposed a stability-monitoring scheme that checks the coefficient after each coefficient update to see if they satisfy some sufficient stable conditions. Li and Qiu [25] developed parameterization method to ensure stability and no stability monitoring is needed.

It is known that a filter is always stable when it satisfies minimum phase condition, in other words, all of its poles and zeros should be inside a unit circle. Hilbert Transform can be used in this sense to get the minimum phase coefficient and monitor the stability of the adaptive IIR filter.

One of the simplest tests of stability is to check after each update of the algorithm that the sum of $|b_j|$ is less than 1[64]. All unstable updates will be detected by this approach, but it can be shown that coefficient space is severely restricted, especially for large M. Jury's test is a more complex method of determining minimum phase polynomial and it does not restrict the coefficient space, but it is not a robust method. Other approaches of testing stability have been suggested, but they are either computationally expensive or nonrobust. The problem is still an ongoing area of research.

In this thesis, the stability of the canceller can be achieved by selecting the step-size sufficiently small without incorporating a monitoring device but slow convergence has to be tolerated.

5-3 Simulation of Adaptive IIR Filter in Noise Cancellation

In this section we present the simulation results of noise cancellation performed by adaptive IIR filter. Here we use a 6^{th} order IIR filter and the same speech signals and white noise signals discussed in Chapter 4. The coefficients were updated using the NLMS algorithm with the adaptive filter coefficients set initially to zero. The resulting signal-to-noise ratio was 20 dB. Comparing this output SNR with that of adaptive FIR filter in chapter 3 where the output SNR is 14 dB, we can conclude that adaptive IIR filter has better performance than its FIR counterpart with the same filter order.

Figure 5.3 shows the learning curve with the input SNR=0. The coefficients trajectories are plotted in Figure 5.4 and Figure 5.5; the convergence is seen to occur within about 30 iterations.

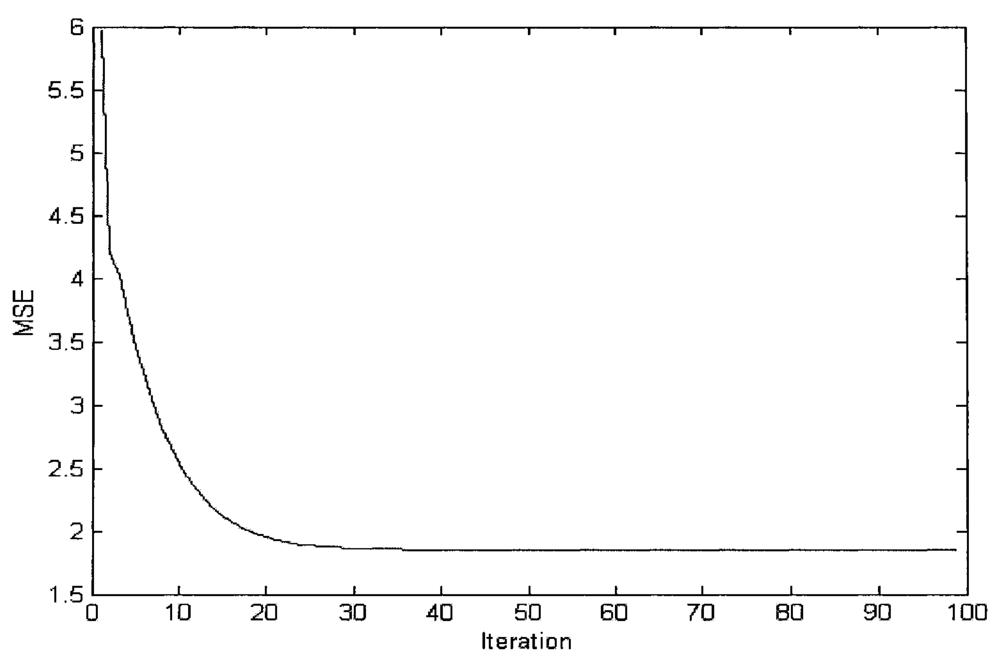

Figure 5.3 Learning curve of adaptive IIR noise canceller

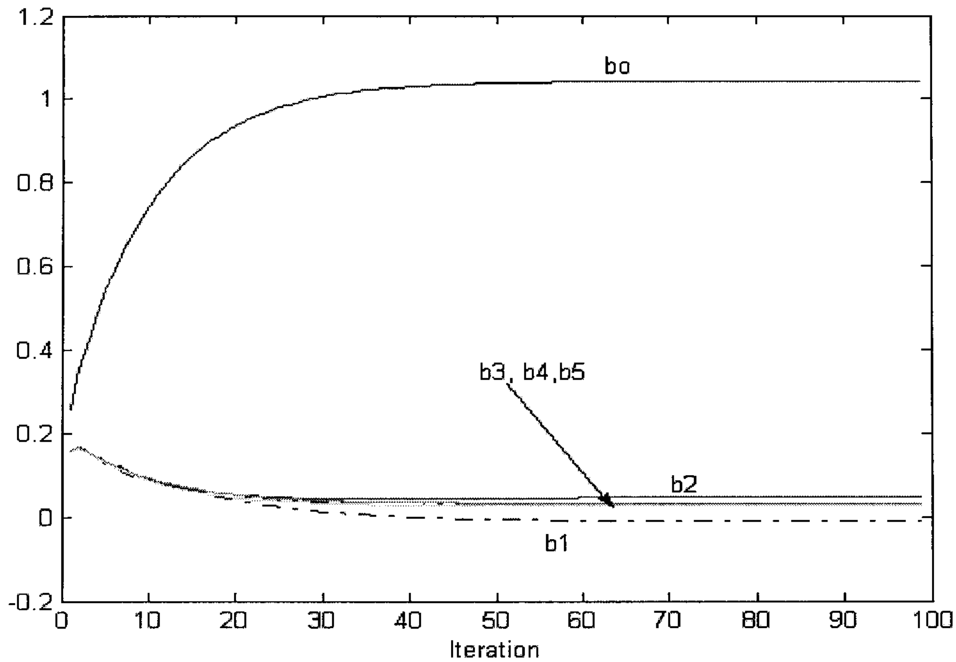

Figure 5.4 Feedforward coefficients trajectories of adaptive IIR filter

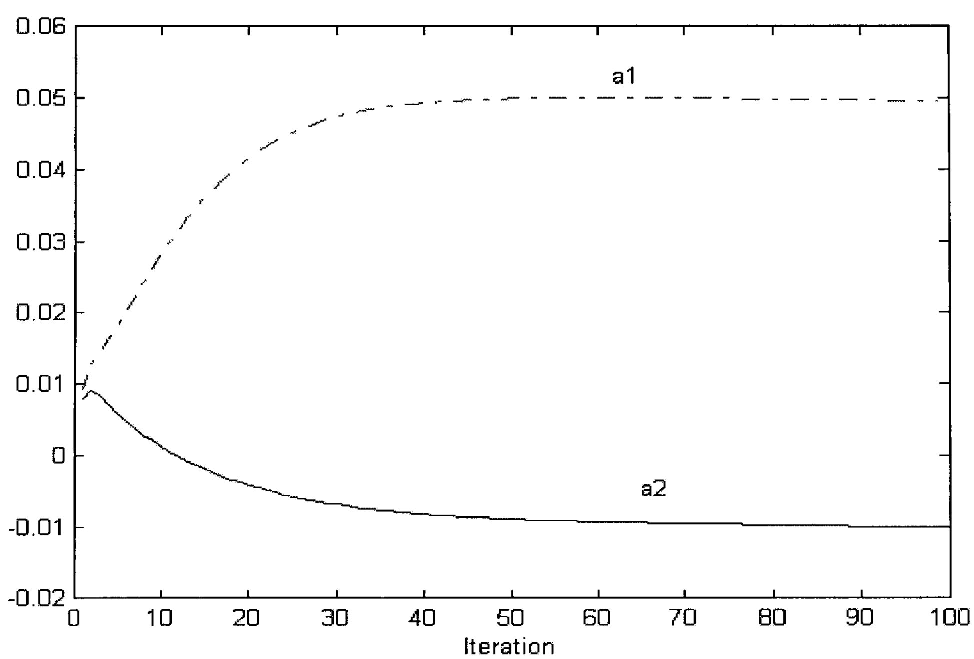

Figure 5.5 Feedback coefficients trajectories of adaptive IIR filter

Figure 5.6 illustrates the comparison of SNR improvements using different noise-free speech signals and reference signals when input SNR is 10 dB. We observe that when the speech signal is s2.wav, the adaptive filter achieves the best output SNR and the maximum output SNR is about 18 dB.

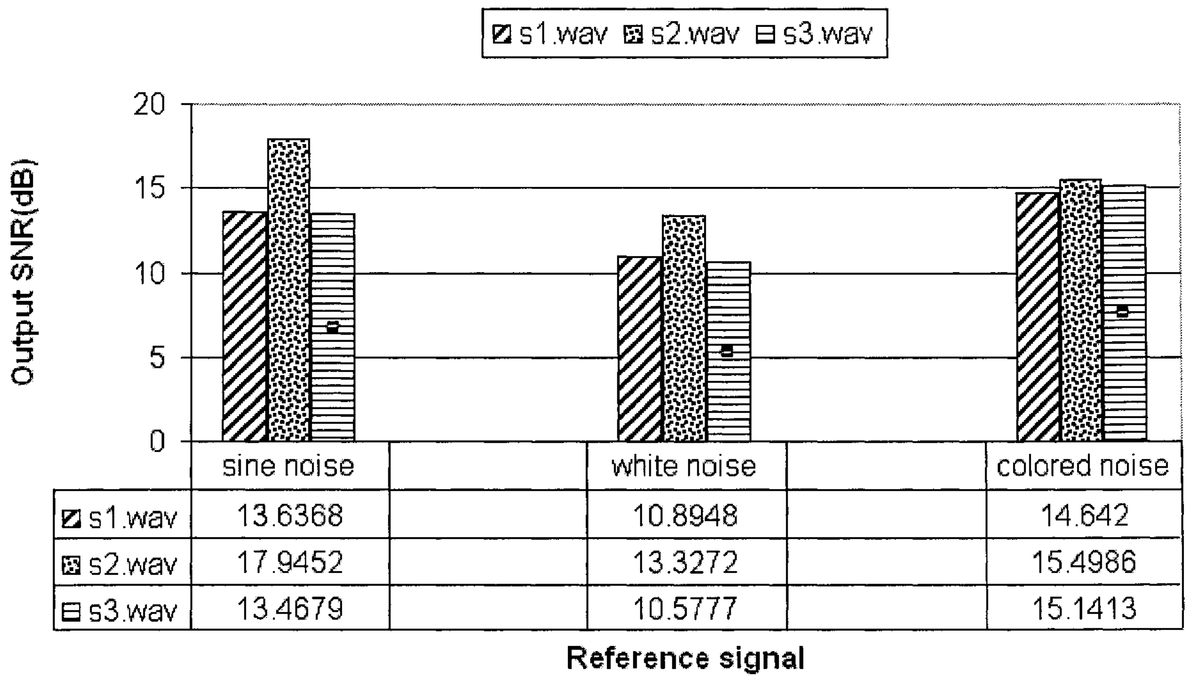

Figure 5.6 Output SNR with different speech signals and reference signals

5-4 Adaptive IIR Echo Canceller

5-4.1 Introduction

The adaptation theory of FIR filters is well developed and has been widely used by researchers on adaptive acoustic echo cancellation. However, in order to achieve an acceptable performance level, FIR filter with several thousands of taps are often required. In the hope of reducing this computational complexity, attempts have been made on adaptive IIR filters concerning echo cancellation. But the adequateness of IIR models for acoustic echo cancellation is a long question, and the answers found in the literature are conflicting [27, 28, 29]. The theory of adaptive recursive filters is still incomplete. Figure 5.7 shows the block diagram of adaptive IIR echo canceller.

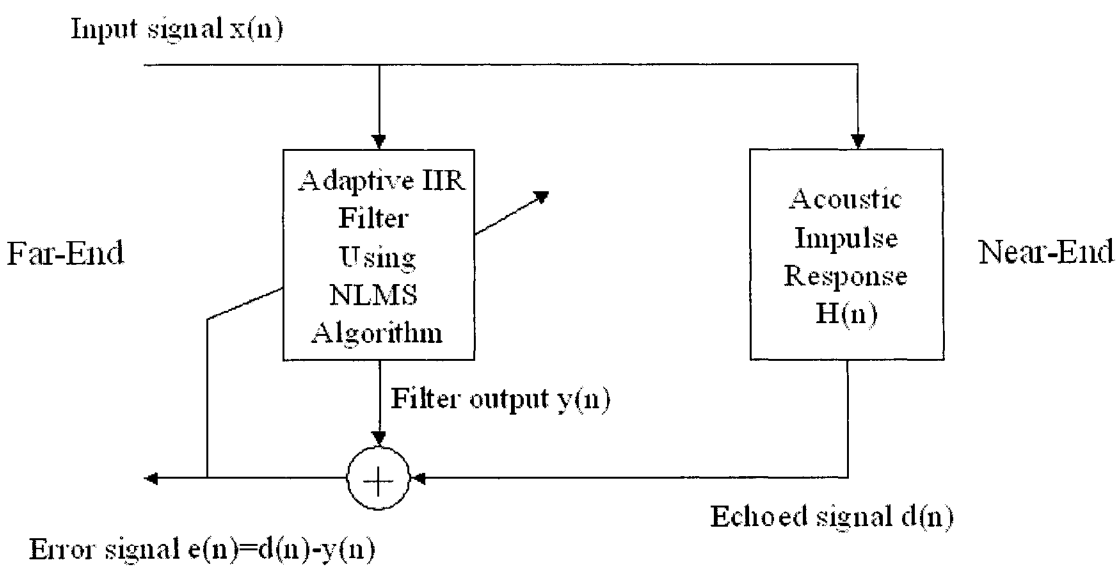

Figure 5.7 Block diagram of IIR echo canceller

5-4.2 Simulations of Adaptive IIR Filter in Echo Cancellation

In this section, we use a 6^{th} order IIR filter to compare the performance on echo cancellation of IIR model versus FIR one.

In Figure 5.8, we plot the output estimation error of the adaptive IIR echo canceller.

In Figure 5.9, we plot the ERLE for the IIR echo canceller.

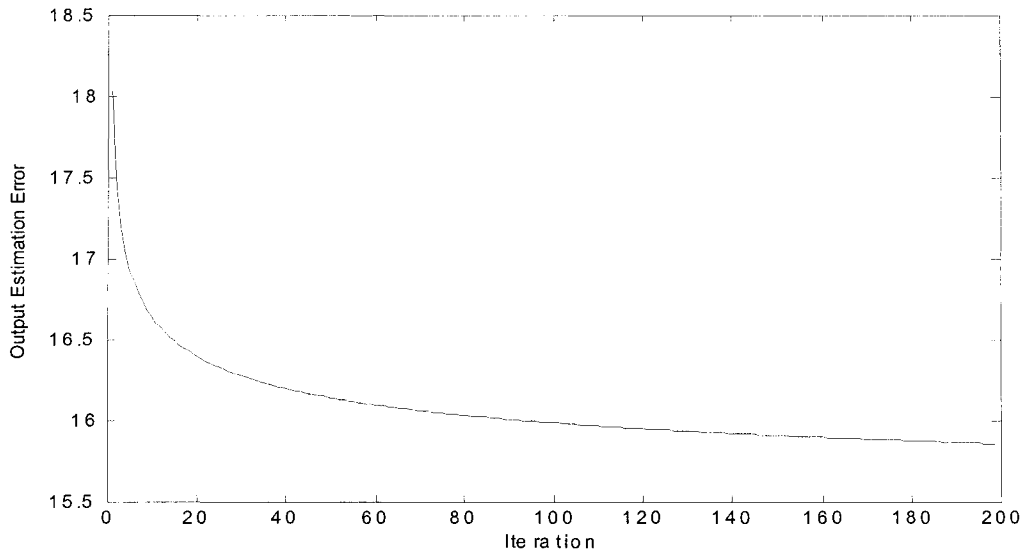

Figure 5.8 Learning curve with input SNR=0

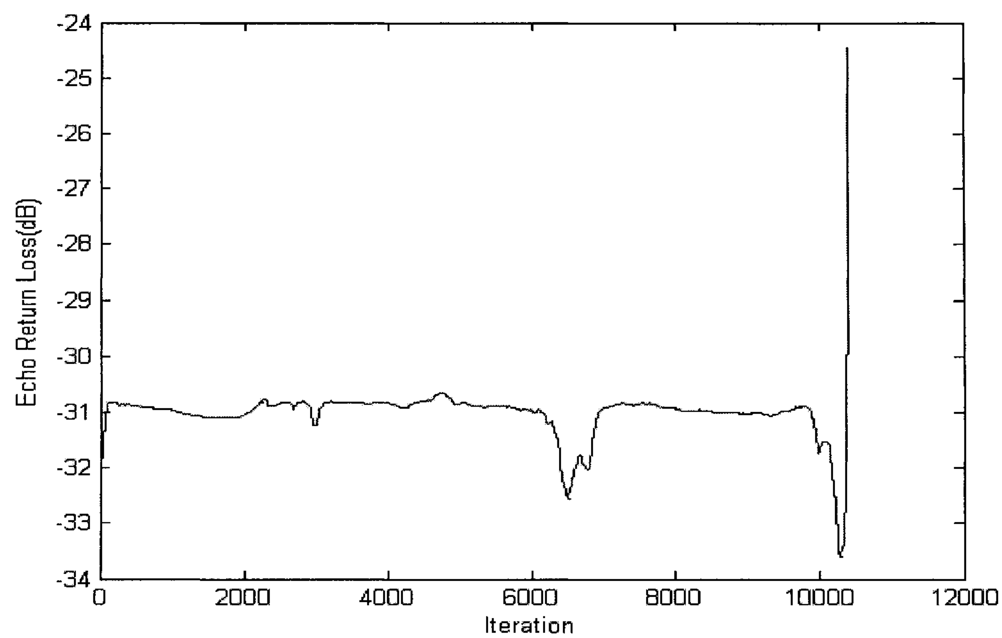

Figure 5.9 ERLE for IIR

Chapter 6

Performance Comparison of Adaptive FIR and IIR Filter

In Chapter 4 and Chapter 5, we have investigated the applications of adaptive FIR and IIR filter and given the computer simulations. In this chapter we will compare the performances of these two adaptive filters under different scenarios. In all the simulations in this chapter, IIR filter and FIR filter are using the same filter coefficients that are 8.

6-1 Noise Cancellation in Speech Signals

In this section, we use the speech signal and white noise signal defined in Chapter 4 as the original and noise signal to do the simulations with adaptive FIR and IIR and compare their performances over different input SNR levels. We use the same room acoustic impulse response defined in Chapter 4. The parameters of filters are listed in Table 6-1. From the table we can see FIR filer and IIR filter have the same number of filter order.

6-1.1 Residue Error (RE)

The residue error is the difference between the original signal and the actual output signal. It is defined as

$$RE(n) = s(n) - e(n), \tag{6.1}$$

Where s(n) is the noise-free original signal and e(n) is the system actual output signal.

Fig. 6-1 to Fig. 6-3 show the residue errors obtained from the IIR filter and FIR filter when the reference signal is white noise and the input SNR is 10 dB under the three different speech input signals. In all these three situations, we observe that IIR filter has a less residue error compare with FIR filter. This means that the IIR noise canceller has a better performance than its FIR counterpart.

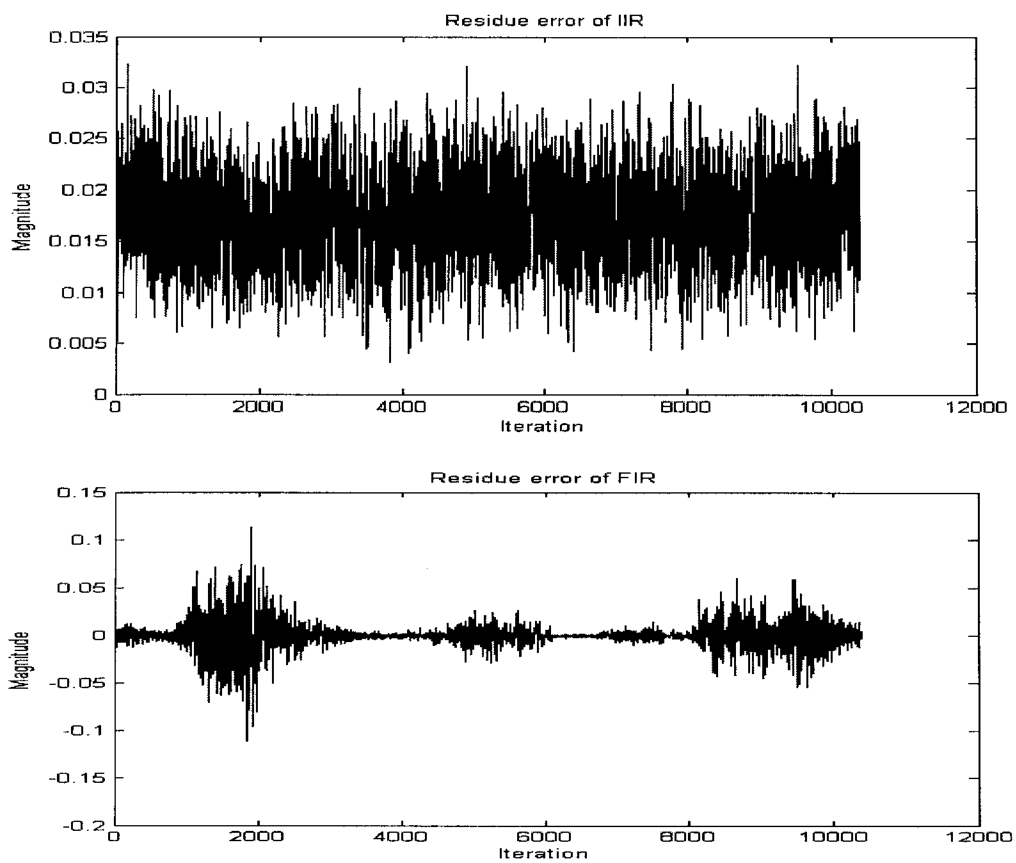

Figure 6.1 RE of IIR/FIR when SNR_{input}=10dB with S1.wave

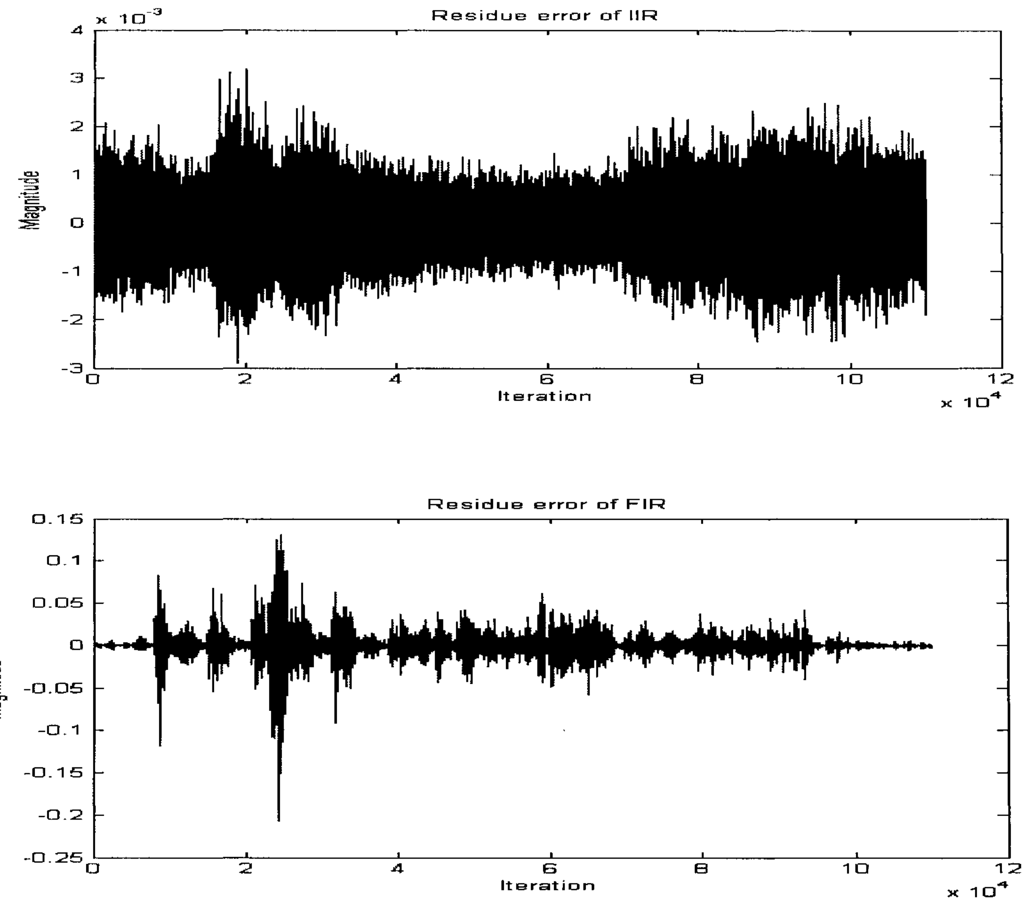

Figure 6.2 RE IIR/FIR when SNR_{input}=10dB with S2.wav

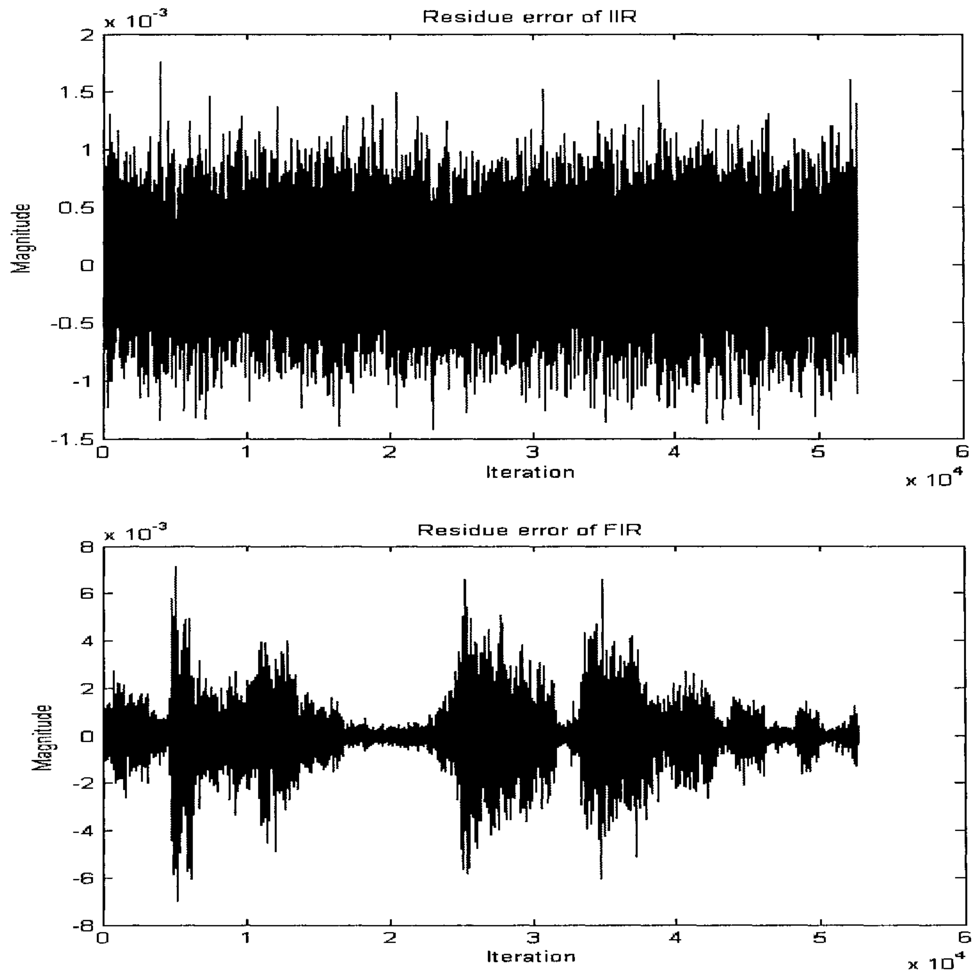

Figure 6.3 RE IIR/FIR when SNR_{input}=10dB with S3.wav

6-1.2 Learning Curves

In Fig. 6.4, we plot the learning curves offered by the models as the function of the iteration numbers when input SNR is 10 dB and the input speech signal is S2.wave. The dashed line plots the mean square error for FIR model, whereas the solid line plots the mean square error achieved by the respective IIR model. We observe that the IIR filter provides a better performance over the FIR filter in this case.

We performed the above simulation with other speech signals and the same result is observed.

Table 6-1 Parameters of filters

Parameter	Value
L	8
μ	0.01
α	0
δ	0.005
μ_1	0.02
μ_2	0.002
N	6
M	2

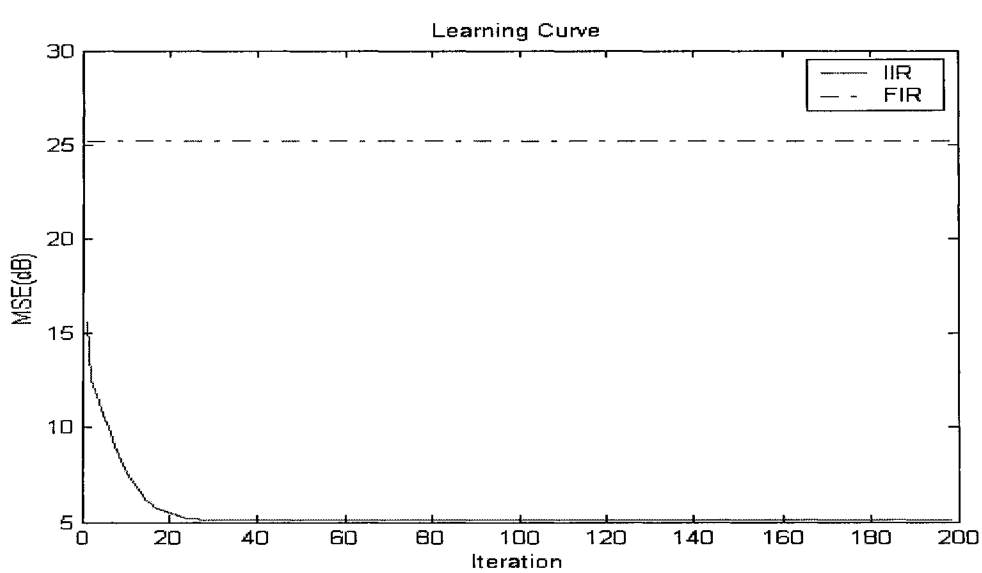

Figure 6.4 FIR and IIR learning curves

6-1.3 SNR Improvement

In Fig. 6.5, we plot the output SNR with different reference signals when input SNR=10dB with S1.wave and white noise, it shows that adaptive FIR filter and its IIR counterpart provide comparable SNR improvement, but IIR filter has better SNR improvement than FIR filter.

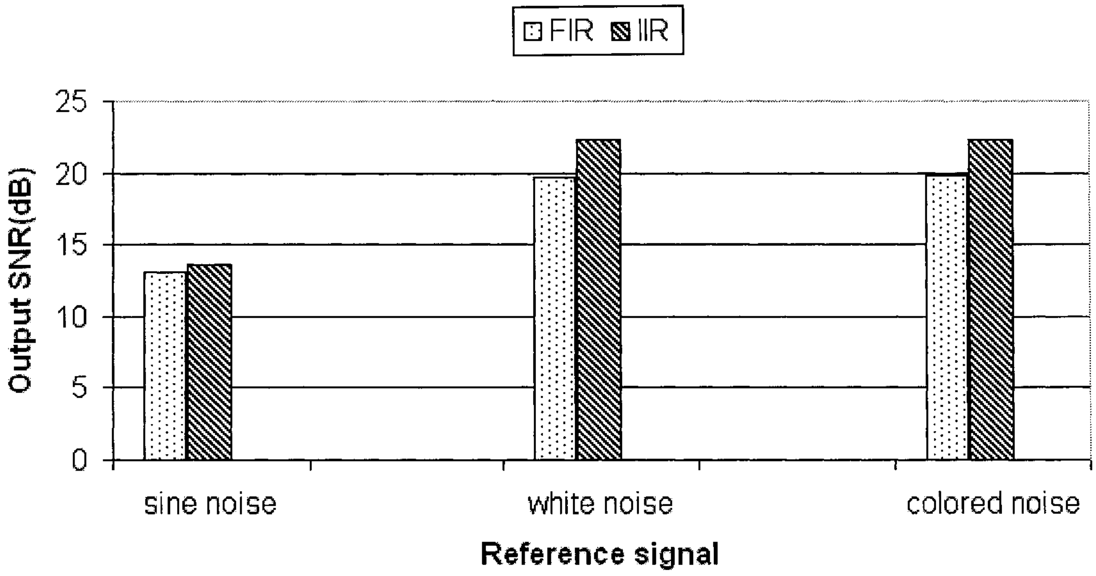

Figure 6.5 Output SNR with different reference signals

6-2 Echo Cancellation

In Fig. 6.6, we plot the output estimation error offered by the models as the function of the iteration numbers when input SNR is 0 dB. The dashed line plots the mean square error for IIR model, whereas the solid line plots the mean square error achieved by the respective FIR model. We observe that the FIR filter provides a better performance over the IIR filter in this case.

In Fig. 6.7, we plot the ERLE curves over the samples. The dashed line plots the ERLE for IIR filter and the solid line plots the ERLE gained by FIR filter. It shows that FIR filter gives a higher ERLE value, which means FIR works well than IIR filter according to this measurement.

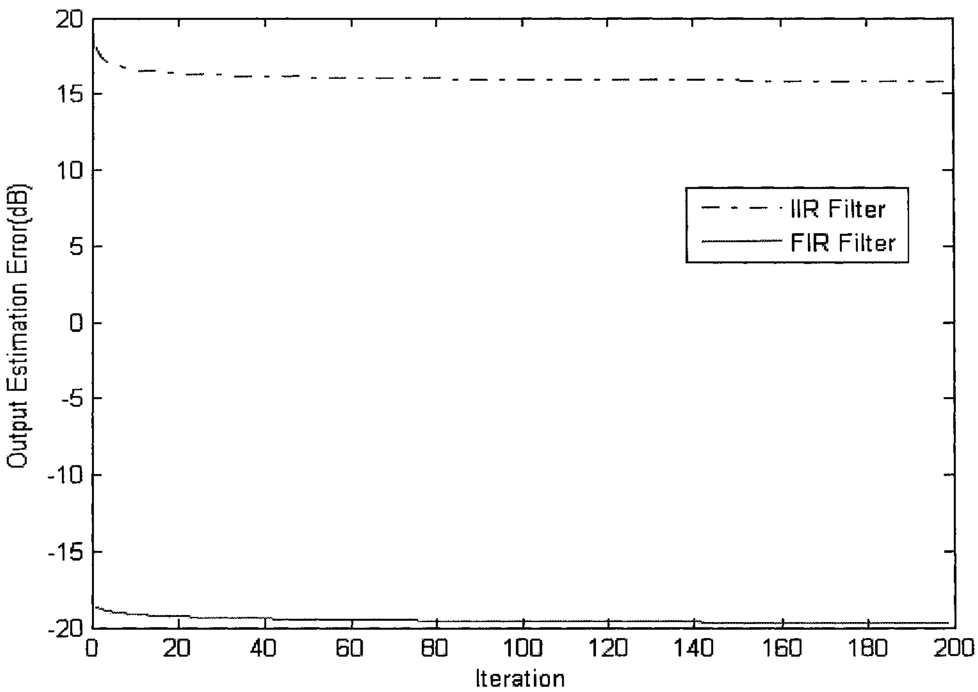

Figure 6.6 FIR and IIR filter output estimation error

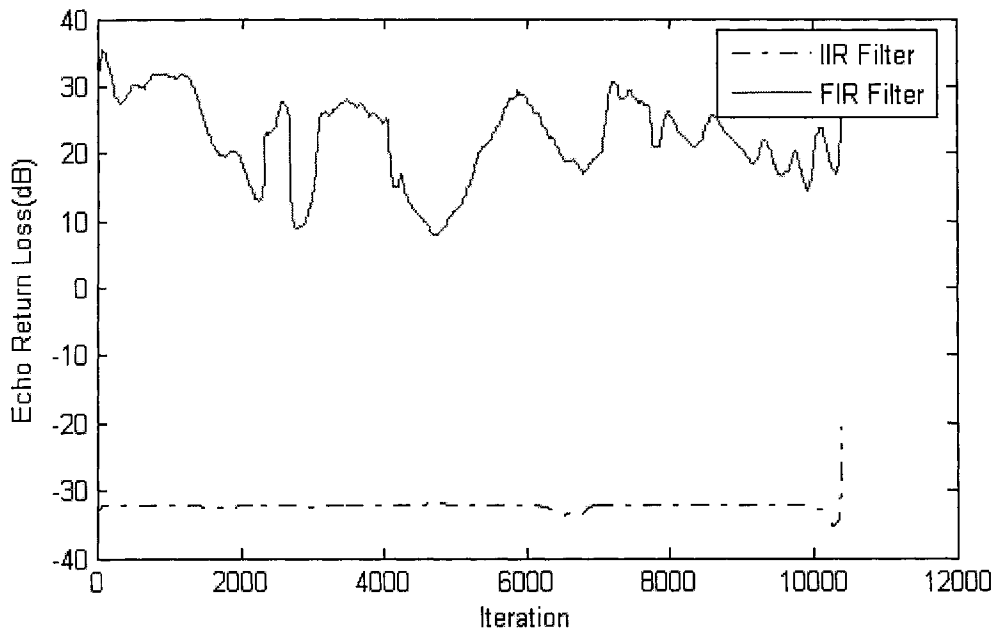

Figure 6.7 FIR and IIR ERLE curves

6-3 Conclusion

We conclude from my simulations in noise cancellation it shows that IIR modes has a better performance than FIR filter, but in the application of echo cancellation IIR model does not outperform its FIR counterparts. The reasons may include some of the follows: i) the orders of the echo path transfer function may not be known exactly [65], ii) the shape of the energy spectra of the acoustic impulse response possess many strong and sharp peaks [27].

Chapter 7

Conclusions

In this study, we focus on the problems of noise and echo cancellation when the corrupted signal is speech signal. Both FIR and IIR filter have been used as the adaptive filter in two cases, where the NLMS algorithm is used as the adaptation scheme.

We presented an overview of the basic concepts of a relatively new technique—adaptive filtering and important structures and algorithms used in this technique and applications in this area in Chapter 1. Then a survey on adaptive noise and echo cancellation was given in Chapter 2 and the adaptive noise/echo canceller and adaptive algorithm were introduced.

Detailed information on the derivation of NLMS algorithm was illustrated in Chapter 3, different algorithms were compared to show that the NLMS algorithm is a best choice since it is simple to implement and its convergence speed is acceptable in the cases in this thesis.

From Chapter 4 to Chapter 6, simulations have been carried out on FIR noise/echo canceller and IIR noise/echo canceller using NLMS algorithm based on their residue error, SNR improvement, output error and ERLE. A comparison on performance of adaptive IIR canceller and its FIR counterpart based on residue error, SNR improvement and ERLE was also presented.

Results of computer simulations using three different speech input signals and three different noises (sinusoidal, white and colored noise) show that by properly choosing the step-size, even with small number of FIR filter coefficients, the noise can be attenuated in an acceptable level. Results also show that increasing the order of FIR filter gives little improvement in speech quality. The results provide the evidence that the adaptive FIR filter is robust against different input SNR.

Results from the simulation on adaptive IIR filter show that the adaptive IIR model has better performance on noise cancellation than the FIR model but not substantially improved.

Simulation results comparing the performance of IIR model and FIR model on echo cancellation demonstrate that FIR filter behaved better than its IIR counterpart.

The theory of adaptive recursive filters is still incomplete. The analysis of the algorithms for adaptive IIR filters is much more complex than that for FIR filters because of the resulting multimodal nature of the MSE surface and the stability monitoring need. Since speech signals encountered in the AEC problem and the AEP are both nonstationary, progress cannot be made until we fully understand simple stationary cases.

Future research can be done on: i) set up some control schemes for the adaptive algorithm to speed up convergence with adding little computational burden; ii) using other structure forms for the IIR canceller rather than the direct form; iii) consider the double talk situation and the problem of ambient noise in echo canceller. In short, a considerable amount of work remains to be done in noise/echo cancellation before the adaptive filtering technique especially the adaptive IIR filtering technique can be put into practical use.

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